Paper to be presented at the

DRUID Society Conference 2014, CBS, Copenhagen, June 16-18

Toward a behavioral theory of open innovation

Oliver Alexy
Technische Universität München
TUM School of Management
o.alexy@tum.de

Elif Bascavusoglu-moreau
University of Cambridge
Centre for Business Research
eb494@cam.ac.uk

Ammon J. Salter
University of Bath
School of Management
a.j.salter@bath.ac.uk

Abstract

Although open innovation has become increasingly established in the management literature, comprehensive theoretical explanations of what drives firms to be open are sparse. By taking the perspective of the behavioral theory of the firm, we conceive of open innovation as a form of non-local search. We argue that firms are prone to use open innovation when substantially under- or overperforming their aspirations. We further enquire how this relationship is moderated by firm-specific assets crucial to innovative activity: human capital, R&D investment, and patenting activity. Operationalizing open innovation as a set of practices, we employ a representative survey of UK firms to test our hypotheses. We find strong evidence of moderation, allowing us both to present explanations for the drivers of search through open innovation as well as contribute to the behavioral theory of the firm itself.

Jelcodes:O32,L25

TOWARD A BEHAVIORAL THEORY OF OPEN INNOVATION

ABSTRACT

Although open innovation has become increasingly established in the management literature, comprehensive theoretical explanations of what drives firms to be open are sparse. By taking the perspective of the behavioral theory of the firm, we conceive of open innovation as a form of non-local search. We argue that firms are prone to use open innovation when substantially under- or overperforming their aspirations. We further enquire how this relationship is moderated by firm-specific assets crucial to innovative activity: human capital, R&D investment, and patenting activity. Operationalizing open innovation as a set of practices, we employ a representative survey of UK firms to test our hypotheses. We find strong evidence of moderation, allowing us both to present explanations for the drivers of search through open innovation as well as contribute to the behavioral theory of the firm itself.

Keywords: open innovation, behavioral theory of the firm, aspiration levels, performance feedback, non-local search, SMEs

INTRODUCTION

Few concepts on the strategy and management of innovation have gathered similar levels of attention as has open innovation—notably from practitioners and researchers alike (Dahlander & Gann, 2010). Defined as "the use of purposive inflows and outflows of knowledge to accelerate internal innovation, and expand the markets for external use of innovation, respectively" (Chesbrough, 2006: 1), open innovation promises to bring about substantial increases in the efficacy and efficiency of R&D, or become an enabler of corporate strategies aimed at generating innovation ecosystems and dominant designs (Alexy et al., 2013a).

At the same time, we know that engagement in open innovation implies substantial organizational change, and is thus subject to significant inertial forces (Chiaroni et al., 2010). Specifically, organizational design and governance structures as well as individual-level routines and job profiles need to be overhauled to full make use of this approach to innovative activity (Alexy et al., 2013b; Foss et al., 2011). Further, opening up innovative activity entails substantial business risk, with companies accidentally disclosing too much potentially rendering their competitive advantage obsolete (Henkel, 2006; West, 2003). In short, at the same time that open innovation offers considerable benefits, it comes at significant costs.

The question that follows for research and managerial practice then of course is: when and why would companies be willing to bear these costs? While many laudable contributions have been made to tackle this question, we note that there is a significant absence of theoretically-motivated work that puts strategic managerial action at the center of attention. One part of the literature looks at drivers of isolated, one-off engagement in open innovation, such as the search for solutions to specific internal problems (Jeppesen & Lakhani, 2010) or the buying and selling of individual technologies on external markets (Arora et al., 2001). Another part of the literature focuses on levels of collaboration (Lee et al., 2010) or external search breadth (Laursen & Salter, 2006; Laursen & Salter, 2014; Love et al., 2011) as proxies for open innovation Yet, although valuable, these approaches offer little insight into the broad range of open innovation practices that firms may use. The literature also explores external triggers that may cause managers to rethink their relative evaluation of closed and open innovation, such as economic crises (Di Minin et al., 2010), industry-level demand shifts (Henkel et al., 2013), or competition between strategic groups (Pacheco-de-Almeida & Zemsky, 2012; Polidoro & Toh, 2011). At the same time, internal drivers of strategic shifts toward open innovation are summarized to consist of managers' overall favorable evaluation of opening up as captured by, for example, a business case (Henkel, 2006). However, such approaches fall short of fully taking into account internal, company-specific attributes that lead managers to consider open innovation in the first place, or why they would evaluate it positively so as to eventually engage in it, as well as the breadth of doing so.

In this paper, we intend to fill this gap by looking at engagement in open innovation through the theoretical lens of the behavioral theory of the firm (Cyert & March, 1963)—hereafter: BTF. We feel this approach is valid given that open innovation is often conceptualized as a *non-local* search process (Laursen & Salter, 2006)—for either technological solutions or market applications—with search also being one of the central concepts of the BTF. Specifically, according to the BTF, firms (or rather: their boundedly-rational managers) set aspiration levels, that is, performance thresholds that the organization should meet. If these aspirations are not met, managers initiate costly, non-local search processes to remedy the situation (problem-based search). Moreover, overfulfillment of aspirations may provide the firm with additional resources, which it may in turn invest into slack-based non-local search to sustain its overperformance (see

Argote & Greve, 2007; Greve, 2003).

Conceptualizing open innovation as search process, we argue that the under- or overachieving of aspiration-levels should also increase firm engagement in open innovation: put differently, managers should consider open innovation as a potential remedy to overcome problems which local search cannot solved (problem-based search) or to foster continuous and potentially sustainable overperformance (slack-based search).

At the same time, we expect this relationship to be moderated by the company's resource base, specifically its human capital, R&D investments and stock of patents. Jointly, these three moderators should present the largest share of inputs that managers may consider leveraging in open innovation processes, yet they should also shape the relationship between companies' aspiration levels and their open innovation engagement differently. Regarding human capital, at high values it may *generally* alter the cost of open innovation search. In this context, Afuah and Tucci (2012) showed how specific open innovation practices increase the search scope of companies. Extending this argument, we maintain that high human capital may enable companies may be able to establish stable conduits to their environment through which they can access external sources even at "normal" levels of aspiration. Concerning past investments, we expect that in particular underperforming companies with a large R&D base will look for help outside their boundaries, whereas over-performing ones should see less need to do so. We further expect that managers apply similar thinking with regards to existing intermediary outputs of R&D, such as patents, that can be brought into open innovation processes.

To test our model, we take a practice-based view on open innovation. To do so, we rely on a bespoke survey instrument, specifically designed to study the open innovation practices of UK small and medium sized companies by the UK Innovation Research Center in 2010 (Cosh &

Zhang, 2011). This unique survey allows us to use richer information compared to previous empirical studies based on Community Innovation Survey type databases, as it collects information on engagements in practices that can clearly be associated with the notion of open innovation. Combining this novel survey instrument with firm-level financial information (from a separate source), we evaluate the relationship between firms' aspiration levels and their engagement in open innovation practices.

Our analysis uncovers patterns largely in line with the hypotheses. While we do not find a direct effect of aspiration levels, we find the predicted U-shaped relationship between aspiration levels and open innovation search behavior for low levels of human capital; at higher levels of human capital, the U-shape flexes toward becoming an inverse U-shape. For R&D investments, we find a turning of the U-shape: for high values of R&D investment, the relationship between aspiration-levels and open innovation resembles a downward-facing hockey stick, yet for low values of R&D investment, the hockey stick largely points upwards. Finally, for patenting activity, we gain surprisingly little traction: neither the quality nor the count of patents has any effect on open innovation behavior. The presence of at least one granted patent has a small, moderating effect on the relationship between aspiration-levels and open innovation behavior. This effect, however, turns out to be contradictory to our initial hypothesizing in the way that underperforming firms with patents use open innovation less than their non-patenting peers.

Our findings allow us to develop three contributions to the literature. First, we present an initial attempt of a behavioral theory of open innovation: a coherent theoretical framework that helps explain drivers of open innovation engagement. By showing how aspiration-levels and firm-idiosyncratic attributes come together to explain firm engagement in open innovation, we substantially extend the literature on the sources of openness (e.g., Di Minin et al., 2010; Henkel et al., 2013) to provide theoretically grounded explanation for intra-industry variation. Second, our findings point toward a more general potential extension of the behavioral theory of the firm itself (Cyert & March, 1963). Specifically, we highlight the uniqueness of firms' search patterns in the context of innovation to shed light on the actual search activity conducted. Extending earlier insights by Afuah and Tucci (2012), we further show how specific search practices as well as internal factors lead to varying levels of perceived costs of collaboration, which in turn extends the scope of local search. Finally, the practice-based view of open innovation we develop may help to improve measurement quality and enhance compatibility between research results in this increasingly important area of study.

THEORY AND HYPOTHESES

Linking the Behavioral Theory of the Firm and Open Innovation

The behavioral theory of the firm (BTF) is fundamentally an explanation of how firms search, and how these decisions to search are based on firm's aspiration levels, which are rooted in their social and historical performance. In its original formulation (Cyert & March, 1963), underperformance lead managers undertake 'problem-based' search, as they sought to respond to impending pressures. In contrast, over-performance led organizations to engage in 'slack-based' search, which involved distant or non-local search (Argote & Greve, 2007; Gavetti et al., 2012; Greve, 2003). The key insight from this theoretical framework is that organizations performing at expected or normal aspirations levels are not likely to engage in search or, at least, will hold constant their search efforts—they would search locally, i.e., within their own boundaries. It is the stretching of the organization by over and under-performance that gives rise to differences with regards to search.

Although this approach has long been a central tenant of managerial theory, it was given renewed impetus by the major growth of theoretical and empirical research about how under and over-performance shaped different aspects of managerial decision-making. In particular, research on the Japanese shipbuilding industry demonstrated that the BFT offered a strong predictor of levels of R&D spending (Audia & Greve, 2006; Greve, 2003, 2007, 2008). This finding was also seen in other sets of industries, suggesting that search—using R&D spending as proxy—was, in part, tied to levels of aspirations based on past and current performance (Chen & Miller, 2007; Chen, 2008). Overtime, scholars have used the BFT to explore other aspects of firm behavior, highlighting the importance of aspirations in shaping network ties in banking (Baum et al., 2005), investments in railroads safety (Baum & Dahlin, 2007), acquisitions (Iyer & Miller, 2008), and corporate illegality (Mishina et al., 2010). Finally, this framework has also been used in studies of entrepreneurship (Wennberg & Holmquist, 2008).

Despite the flexibility and empirical validation of this intellectual framework, the increasingly wide scope of studies that link under and over-performance to managerial decision-making raises questions about the domain of the BFT. In particular, since the BFT is largely a theory of organizational search, it offers unique insights into the decisions of firms with regards to their efforts to find solutions to problems. However, the nature of this search – whether it is through internal investments, collaboration, networks, expenditures on R&D, acquisitions etc. – is less clear. The attraction of the BFT to other areas of decision-making are obvious, as it provides a strong framework for developing predictions about firm behavior in a number of non-obvious domains areas, some of which fall well outside the original scope of the theory.

In this paper, we return to one of the central elements in the BTF—the link between aspiration levels and actual search *behavior*. While search behavior is a central tenet in the BTF

(Cyert & March, 1963) and related theories (Nelson & Winter, 1982), reviews of the BTF make clear how most theorizing related to the BTF is about the search process on a fairly abstract level (Argote & Greve, 2007; Gavetti et al., 2012): for example, literature in the N-K tradition, while talking explicitly about local and non-local search, never looks at how firms are *actually* searching, that is, the actual practices they engage in. Similarly, other literature links aspiration-levels to changes in behavior, and postulates the changes to originate from search processes, yet again without these actual search activities being directly examined. While notably exceptions exist (e.g., Gavetti & Rivkin, 2007; Maggitti et al., 2013), by and large, the practices and processes that firms use for problem-based and slack-based search remain underexplored.

Accordingly, we focus on firms' use of open innovation as a lens to better understand how search is manifested as an organization's adoption of a set of managerial practices to harness external pathways to knowledge creation and exploitation. Central to this formulation, open innovation has been often been described as a non-local search activity (e.g., Afuah & Tucci, 2012; Laursen & Salter, 2006). This is because it involves the firm making new efforts to search externally for technology and/or market knowledge (von Hippel, 1988; Alexy et al., 2013b). Specifically, as for non-local search in the BTF, firms will resort to open innovation to tackle technological or market problems they cannot solve on their own. In turn, a wide variety of practices of non-local search using open innovation exist, including for example crowdsourcing (Afuah & Tucci, 2012), innovation intermediaries (Jeppesen & Lakhani, 2010), markets for technologies (Arora et al., 2001), and even patent auctions (Fischer & Leidinger, 2014).

Predicting Firm Engagement in Open Innovation Practices

In this paper, our attempt is to explain the degree (or breadth, see Laursen & Salter, 2006) of a firm's activity in open innovation. To do so, we take a practice-based view on open innovation—that is we define open innovation as a set of different and often complementary practices that firms will apply to solve innovation-related problems. In doing so, we also hope to overcome a shortcoming in the recent open innovation literature, which—despite considerable advances—has presented varying definitions and operationalizations of open innovation, which were often hard to separate from related constructs, such the firm's attempts to absorb external knowledge and/or its collaboration strategy. Others have focused on open innovation using a measure of in and out-licensing of technology (Fosfuri, 2006) or co-patenting (Belderbos et al., 2014). We argue that such approach must remain incomplete, as they will fail to capture the wider set of managerial practices associated with open innovation, which include a broader range of efforts that external search, collaboration, licensing and co-patenting. Moreover, these studies may confuse the drivers of specific forms of external engagement with the set of practices associated open innovation. For instance, the drivers of licensing may differ considerably from a firm's decision to engage in open source software or to work with lead users.

Following such a practice-based approach, our baseline hypothesis rests on a core tenet of the BTF: bringing together the BFT with the literature on open innovation, we suggest that under and over-performance relative to aspirations will lead to greater use of open innovation practices. Below, we focus first on the underperformance case before turning to the over-performance case.

Fundamentally, firms performing below aspirations will be under pressure to identify solutions to near-term problems, as they need to find a way to return to higher relative performance. As such, open innovation provides a means for underperforming firms to gain access to new resources that augment their own. Moreover, as the firm's performance deviates significantly from its aspirational level, it is liable to become increasingly desperate in seeking these external resources, as only they may provide a key to return the firm to its aspiration level.

Underperformance may also lead the organization to seek the help of external actors to help commercialize their ideas. In contrast, a firm that is performing near or at its aspiration levels has little incentive to engage with external actors, preferring to 'go-it-alone' in its innovation efforts. In this context, it can be expected that the extent of open innovation practices a firm engages in is associated with their degree of underperformance relative to their aspiration levels.

In the case of overperformance, firms are liable to surfeit of resources, which will enable them to allow individuals and teams to engage in 'slack search', activities that break away from organizational accountability and may even be considered 'foolish' (Levinthal & March, 1981; March, 2006). As such, overperforming organizations have slack resources that using which staff may undertake playful projects: activities not directly subject to organizational monitoring, measurement, or selection. For example, Google—by any measure an over-performing organization—allows its staff to take 20 per cent of their time for their personal projects, and many of these personal projects involve open innovation initiatives to work with outside partners (Iyer & Davenport, 2008). In this context, open innovation practices are especially germane to enable slack search, given they provide opportunities for organizational members to tap into new areas through collaboration with external actors. External actors' knowledge domains and practices are liable to differ considerably from the focus organization, and therefore they are attractive for partners in generating greater combinatorial novelty. In contrast, internal search efforts are always limited by the nature of knowledge possess by the organization, and therefore may are liable to be more combinatorially constrained (e.g., Fleming, 2001).

Taken together, in contexts where a firm is performing significantly above or below its aspirations, we expect that they display high levels of engagement in open innovation.

H1a. Under-performing firms will exhibit higher levels of open innovation activities.

H1b. Over-performing firms will exhibit higher levels of open innovation activities.

The Effect of Firm Resources on Open Innovation Activity

Although the previous discussion locates the use of open innovation practices in the context of firm performance, it says little about how the firm's resources and capabilities may shape its openness when it has under and overperformance relative to its aspirations. In order to enrich our understanding of the influence of these resources, we focus on the potential effects of three key innovation-related resources: a firm's human capital, its R&D investment, and its patenting activity. Each of these variables has been found to be important in explaining open innovation, as they provide a key set of resources to help the firm be effective at engaging external actors (e.g., Alexy et al., 2013b; Fosfuri et al., 2008; Foss et al., 2011). However, the impact of these three technological resources on open innovation in the context of under and overperformance has not yet been examined. Moreover, it is not clear to what extent these resources may overcome the saliency of under and overperformance relative to aspirations, as drivers of search and therefore open innovation. Below, we take each of these three areas in turn.

The role of human capital

It is clear that a firm's human capital—the skills and talents of its employees—may play a primary role in shaping the firm's ability to search externally. Without skilled staff, firms would lack the prior knowledge and experience to successfully absorb and utilize external knowledge (Cohen & Levinthal, 1990). High human capital also makes a firm a more attractive partner for external actors and an organization can draw upon its skilled employee's extensive social capital to reach out to external actors (Coleman, 1988). Indeed, prior research has shown that the level of human capital of a firm is associated with a variety of measures of open innovation (Escribano et al., 2009). However, the importance of human capital for open innovation in the context of under and over performance relative to aspirations is unstudied.

We argue that human capital may also alter the way firms perceive under and over performance and mitigate the effect of aspiration levels on open innovation. Fundamentally, human capital represents a (semi)permanent conduit to engage external sources (Podolny, 2001; Powell et al., 1996). As such, the existing networks that individuals with high human capital will bring may be used to lower the costs of absorbing knowledge from external sources (Rosenberg, 1990), and therefore alleviate the tendency of under and overperforming firms to seek to augment local capabilities with external actors. Simply put, with such networks in place, non-local search is *always* (relatively) cheap to the organization, so it should not take problems or slack to overcome associated perceived hurdles. Similarly, human capital also represents an endowment for using external knowledge that is available for use irrespective of the organization's current performance levels. Like a radio frequency, it is an organizational capability that is always turned on, and therefore performance relative to aspirations may be less salient in motivating organizational search choices in its presence. Finally, firms with high levels of human capital are liable to have a strong repertoire of external contacts and relationships that they may draw on in times of crisis and therefore should have less of a need to engage in a wider range of open innovation practices as aspirations levels fall below or rise above expected levels.

To summarize, for firms with high human capital, we expect that these, on the one hand, may engage in non-local search absent the conditions of under and overperformance. At the same time, in case of under or overperformance, no particular relative increase in search activity should be expected. For these reasons, we would expect at high levels of human capital the effect of under and overperformance on open innovation would flatten, indicating that open innovation would less tied to past performance.

H2. At higher levels of human capital, the strength of the relationship between under/overperformance and the level of open innovation activity will decrease

The effect of R&D investments

The importance of investment in R&D for open innovation and external search has long been acknowledged in the literature (Chesbrough, 2003). R&D creates new knowledge that firms can exploit themselves or in collaboration with others. Internal R&D endeavors remain critical for open innovation, as they provide outputs—such as specific knowledge or solutions—that firms can use to engage external parties as well as knowledge fostering understanding of what is going on in the outside world. By investing in R&D, firms are not only generating new products, processes and services, they are also creating the capability to better exploit external knowledge (Cohen & Levinthal, 1990). R&D itself may also spur open innovation, as when firms may need to find solutions to problems that are distant from their current body of knowledge (Afuah & Tucci, 2012; Jeppesen & Lakhani, 2010). In addition, expenditures on R&D provide a potential opportunity to develop technologies that can be traded in markets for technology (Arora et al., 2001). Finally, R&D makes a firm a more attractive partner for externals, as it is signal of the quality of the firm that it may possess useful resources that external actors may acquire or exchange (Laursen and Salter, 2014). For these reasons, it can be expected that R&D is a positive contributor to greater levels of open innovation.

The role of R&D for open innovation in the context of under and overperformance relative to aspirations is less well understood. We argue that past R&D efforts may substantially affect how firms interpret past performance with respect to future search efforts in open innovation. To illustrate our point, we stylistically distinguish four extreme cases: whether firms are under- or overperforming, and whether they are low or high in R&D investment.

In the case of low R&D-intensive and underperforming firms, it can be expected that these organizations will be unable to reach to external actors through open innovation. Not only do they lack the necessary internal resources to engage in open innovation, they are also unattractive partners given they are poor performers and have limited R&D resources to be added to an open innovation relationship. In the case of high levels of R&D expenditures and underperformance, however, these patterns are liable to be reversed. In this context, unsuccessful but R&D-intensive firms can and will seek help from external actors, given they have both the means and motive to do so. Their investments in R&D will make them attractive partners to externals and their underperformance desperate to find and accept help; therefore they should be more successful in finding external partners within with to work with on open innovation efforts.

In the case of overperformance, we would expect that the importance of R&D is less salient. High-performing organizations with little or no R&D may have other resources that make them successful, and therefore may have alternative pathways to engage in open innovation. In addition, their performance trajectory makes them attractive partners despite their lack of formal R&D efforts. Accordingly, we would not expect that R&D shapes open innovation in the context of over-performance relative to aspirations.

> *H3. The level of past R&D expenditure affect open innovation, so that underperforming firms with high R&D expenditures will engage in more open innovation than firms with low R&D expenditure.*

The effect of patenting activity

In order to engage in open innovation, firms often need to ensure they have formal intellectual property (Chesbrough, 2006; Laursen and Salter, 2014). Intellectual property, such as patents, has been described as the currency of open innovation, because its possession allows organizations to engage in markets for technology (Arora et al., 2001)—IP may be seen as a trading chip required to be allowed to participate in such processes (Hall & Ziedonis, 2001).

Formal IP also allows organizations to more successfully collaborate with other organizations, which may require formal IP to be in place before engaging into collaboration with an external party. In particular, large firms tend to prefer partners with patents because they seek to ensure downstream value capture of these collaborations and clarity about the ownership of inventions (Alexy et al., 2012). In addition, the possession of IP is a (weak) signal of firm quality, suggesting that the firm has valuable inventions that have been upheld by an external body (the patent office). As such, the possession of patents is liable to have a positive effect on firm openness in general.

The possession of patents may also moderate the effect of past performance on open innovation. The logic here is akin to the preceding hypotheses (with the difference that patents are usually an output of R&D in the search of a market, and past R&D may rather require other firms' R&D assistance in further technological development): for firms with little or no patents and who have been underperforming, they have limited scope to engage in open innovation, even if they were able and wanted to. This is because although underperformance may force them to seek external resources, these organizations will have little to trade in the market for technology. Moreover, they will be unable to find partners because they lack the signal of quality and potential appropriation that patents provide. As such, they may be frozen out of open innovation opportunities. In contrast, firms with patents that have underperformed may still find scope to successfully engage in open innovation. These firms will have assets to trade, and may be able to leverage these assets to entice collaborators to help them reach their performance aspirations. In effect, patents will provide these underperforming firms with a vehicle to openness. Finally, for the case of over-performance, we would again expect the value of patents for open innovation to be of little importance, as these firms have other compensating mechanisms to allow them to engage in open innovation.

> *H4. The level of a firm's patent activity will affect its degree of open innovation, so that underperforming firms with patents will engage more in open innovation than firms with no patents.*

DATA AND METHODS

Empirical Context and Survey Design

Open innovation pertains to a wide variety of sectors, both in manufacturing as well as in services (Chesbrough, 2003; Chesbrough, 2011). It should be particularly prominent when value creation is complex and thus split amongst actors in the value chain, who specialize in order to to master technological difficulties or decrease the cost necessary to keep up with technological progress. In addition, open innovation should happen in small and large firms alike (van de Vrande et al., 2009): while large firms have more resource to offer in open innovation relationships and to manage them subsequently, small firms, due to their liabilities of smallness, will more often need to search beyond their boundaries for solutions to their innovation related problems.

As such, we chose to rely on a survey instrument that systematically sampled small and medium-sized technology and service firms in the UK, at the same time following a practice-based approach to open innovation. Specifically, the data we use in this paper are drawn from the UK~IRC Open Innovation Survey, purposefully designed and launched in 2010 to study the open innovation practices of UK small and medium sized companies.

This survey used systematic random sampling to draw a sample of 12,000 UK firms with between 5 and 999 employees from Bureau van Dijk's FAME Database, which also contains detailed financial company-level information on UK and Irish businesses. After carrying out pilot tests in different size groups and sectors, five waves of questionnaires were sent out by post between June and November 2010.[1] 1,202 firms completed the survey, leading to a 10% response rate. FAME Data has been used to check for non-response bias, and no significant difference was found between respondents and non-respondents in terms of size, turnover, and year of firm formation (Cosh & Zhang, 2011).[2]

Sample

In this study, we can draw on a sample size of 386 firms, due to number of reasons. First of all, 245 firms who completed a shorter version of the survey had to be excluded. Another 45 firms were deleted due to incomplete responses. Finally, a further 504 firms had been removed in the process of matching the survey data with the latest wave of the FAME dataset. That is, these firms were too young to have the track record that is needed to create measures for aspiration-levels (see below).

Between the original sample of 1,202 firms and our final database, we have found some attrition bias: firms in our final sample are on average larger, with higher R&D expenditures and a higher share of human capital. Also, compared to the original dataset, firms with 100-500 employees are over-represented in our sample. Finally, we also see some differences in the structure of our dependent variable. We will attend to the latter issue by used weights on observations, and discuss this with the other robustness checks below.

Variables

Crucially, we use two sources of data for our study. Not only does this allow us to minimize issues of common method bias {Podsakoff, 2003 #774}, we can also lag all independent variables to capture them for the time *before* the survey. Specifically, we draw the

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1 For waves 1-3, the original 12-pages long questionnaire was sent out; however, in order to increase the response rate, shorter versions have been sent for the following waves.

2 Except for the conventional business services, where respondents have been found to have a significantly smaller turnover than the non-respondents.

dependent variable from the survey questions which pertain to the years 2008 to 2010. In turn, the core independent variables are taken from publicly available sources, most notably the FAME database, for the year prior to 2008.

Dependent variables.

The dependent variable in our study is *open innovation breadth (OI Breadth)*, captured by the number of different open innovation practices the firm engages in. Specifically, firms were asked to indicate the use of various informal and/or formal activities with external parties, in order to accelerate innovation. These activities are listed in the Appendix. The scope of open innovation activities is computed by using a “breadth” measure, by adding up these 15 activities, following previous literature (Laursen & Salter, 2006; Leiponen & Helfat, 2010). The resulting open innovation variable has a high degree of internal consistency with a Cronbach’s alpha of 0.86. Around 20% of our sample does not practice any open innovation activities, whereas only 2% is engaged in all 15 activities. Given that the decision whether or not to engage in open innovation may be the result of a preceding selection decision, we will also model this sample selection as a robustness check. In addition, we observe significant variance in the specific practices chosen by firms, with some (costlier) practices selected very few times over all. To account for this variation in practice selection within the population, we further produced a *weighted index of OI practices*, in which the selection of a practice used rarely by the rest of the sample scored more highly than the choice of a commonly used one (see Bozeman & Gaughan, 2007). This approach helps ensure that our measure of open innovation practices is assessed not just by a firm’s use of the most common practices, but also by their use of less frequent (and most costly) practices.

Independent variables.

The first of our key independent variable are the *aspiration levels*. Following Greve (2007), we constructed the aspiration level variables as a combination of a social and a historical aspiration level. The social aspiration (SAP) level is derived from the firm's past performance relative to the average of other firms' performance who are seen as competitors. Following the literature, we measure performance as sales growth, and define the peer group at the 4 digit SIC level by drawing on data from the Office of National Statistics. The historical aspiration (HAP) level is a weighted average of the past historical aspiration levels and the past performance of the same firm. The performance is measured by the return on assets (ROA), defined as the operating income divided by the total assets.

$$SAP_{it} = \Sigma G_{it} / N\text{-}1$$

$$HAP_{it} = \alpha HAP_{it-1} + (1 - \alpha) P_{it-1}$$

Here, G is the industry sales growth, P is firm performance, and t and i/j represent time and firm subscripts. α has been estimated to 0.1 using a grid search and taking the combination with the highest model likelihood (Greve, 2003). The final aspiration level is constructed following:

$$A_{it} = a_1 SAP_{it} + a_2 HAP_{it}$$

The weights a_1 and a_2 are again estimated by a grid search (by increments of 0.1) and yield to 0.77 for a_1 and 0.23 for a_2.

As to the remaining independent variables, *human capital* is measured by the share of employees with a higher education degree. Given that we are interested in intermediate outputs of R&D, we chose to operationalize *R&D investments* (logged) using R&D expenditures, rather than intensity. Finally, for *patenting activity*, we employed several operationalizations: whether the firm patented or not (dummy), the firms' patent stock (count), and a quality-controlled measure that also incorporates the citations their patents have received.

Of course, our interest lies not in the direct effect of these variables, but in their interaction with those capturing aspiration levels. In constructing these, we mean-centered the human capital and R&D investments variables to ease interpretation of the respective coefficients—notably, this is a purely mathematical procedure that has no other effects (Echambadi et al., 2006; Echambadi & Hess, 2007).

Control variables.

We further include measures for *firm size* and *age*. Larger firms may be expected to have greater resources to engage in open innovation than smaller firms. Young firms may lack time to build external relationships, and therefore are less likely to engage in open innovation. Next, *absorbed slack* is measured as the ratio of selling, general, and administrative expenses to sales (George, 2005). We also control for the *sectoral technological intensity* by introducing dummy variables for high-tech, medium-tech manufacturing and traditional business services and knowledge intensive business services, the reference category is the low-tech manufacturing.

Modeling and Estimation Strategy and Sources of Bias

We test our hypothesis using zero-inflated negative binomial (ZINB) estimations, due to over-dispersion of the dependent variable OI Breadth and the large share of firms with no open innovation activities in our sample. Both a Vuong test and the AIC suggest that we should prefer the use of ZINB against other count data models, which we keep as robustness checks. In addition to the control variables, we introduce in the inflated model the perceived competitive pressure, measured by the number of competitors, a self-reported sales revenue growth objective (from the survey), and an industry-level formal IP protection measure (Cassiman & Veugelers, 2006). The first two of these measures are taken from the survey, and are self-reported. The measure of industry IP is an aggregate of the use of formal protection mechanisms across the survey responses by industry. In order to account for unobservable heterogeneity, the standard errors were clustered by 2-digit industry codes.

Regarding common method bias, the use of different data sources such as FAME alongside the original survey already significantly limits any threat of common method bias in our estimations (Podsakoff et al., 2003). In addition, in the survey design, all recommended design elements to reduce bias were accounted for. Finally, we also applied standard tests, such as Harman's one factor test, and find no indication for common method bias.

In addition, we performed all useful standard tests of multicollinearity (Echambadi et al., 2006; Echambadi & Hess, 2007), using unstandardized data to do so. We were happy to find high correlations and changes in coefficients between estimation models only to be caused by the interaction terms—which is of course to be expected. Given that even the introduction of interaction terms into our models has negligible effects on the t-statistics of other, unrelated variables, we conclude that our findings should not substantially suffer from multicollinearity.

RESULTS

--- *Insert Table 1 about here* ---

Before turning to our multivariate analysis, we first take a look at the descriptive statistics of our variables of interest, which are reported in Table 1 . Most importantly, we find that all our variables of interest show sufficient variance, and that a significant share of observations for each variable lies toward the extreme values of a variable. This finding is reassuring, in particular with regards to the interpretation of interaction terms.

Table 2 contains the results of the ZINB regressions. Model 1 contains only the baseline terms. In Model 2, we add the aspiration-level main effects for under- and overperformance.

Models 3, 4, and 5 separately introduce the interaction terms with human capital, R&D investment, and patenting activity, respectively. We use these models mainly to look at individual improvement of model fit from the interaction terms (which is significant in all cases). Finally, Model 6 contains the full model—it is the basis of our hypotheses tests and underlies the simulation results (Zelner, 2009) shown in Figures 1 to 3. Notably, however, given that we cannot estimate zero-inflated negative binomial regressions using this method, the figures are reporting the results of simple OLS regressions. Alternatively, we also employed standard negative binomial regression as well as the approach suggested by Brambor and co-authors (2006). Furthermore, we also simulated the OLS regressions using a logged version of the dependent variable. All results are consistent with the figures shown herein.

--- *Insert Table 2 and Figures 1 to 3 about here* ---

Given the complexity of our hypotheses, a simple interpretation of the coefficients in Table 2 (in particular Model 6) makes little sense. Still, a quick look at Model 2 suggests that our baselines hypotheses H1a and H1b should not be accepted. Turning to the other hypotheses, we note that all interactions, individually introduced (Models 3-5) improve model fit and seem to gain some empirical traction. As to the deeper meaning of this, we look at the simulation results. Figure 1 clearly indicates how for low levels of human capital, we actually find the search patterns predicted by the behavioral theory of the firm. Oppositely, as predicted by H2, these patterns disappear for firms with high level of human capital. In fact, we find that these search significantly less at low levels of performance *and* search significantly more at average levels of performance—the difference for over-performance is not significant. Looking at Figure 2, we also see that underperforming firm with high levels of past R&D investment are more likely to engage in open innovation search in the present, lending support to H3. Finally, for H4, we find results opposite to what we predicted: rather than resembling the results for R&D investment (H3), the joint effects of patenting activity and aspiration levels resemble those for human capital (H2). As such, it seems as if the logic of conduits that we attributed to individuals with high human capital seem to extend to patents as well. However, when we replace the dummy variable with more accurate representations of patenting activity (a simple patent count or a citation-weighed count), the difference between the lines completely disappears. Accordingly, we do not want to over-interpret the effect we find, and simply note that we cannot reject the null hypothesis with regard to H4.

Robustness Checks

To corroborate our findings, we engage in a series of robustness checks. First, we applied a series of additional estimation methods, including negative binomial regression and OLS. In addition, we explicitly tried to account for firms' decision to engage in open innovation by modeling it as a two-step process. We first predicted firms' decision to engage in open innovation activity at all (using the same variables as for the zero inflation) and included the resulting inverse Mill's ratio in a second step: a zero-truncated negative binomial model (tnbreg in Stata), also checked against a simple OLS specification. We find that, across all these specifications, our results remain qualitatively identical.

Second, we ran several checks on our dependent variable. We began by applying weights to our regression to account for the differences in the distribution of the dependent variable when comparing our sample and all 1,202 original survey responses. Next, we used the "weighted index" version of the dependent variable described above—notably, while the first method described in this paragraph puts weights on a full observation, this approach puts a score on a specific type of open innovation search, the value of which is higher the less often the practice is chosen by all sample firms. Finally, we also split the dependent variable according to whether a search practice may be regarded as formal-contractual or informal. Then, we reran all estimation method described in the previous paragraph (as well as all simulation approaches and their respective robustness checks, described above) where applicable (the index is of course not a count variable), using the three alternative specifications of the DV. Again, results remained qualitatively unchanged—to our surprise, there were not even any major differences between formal and informal practices (cf. Grimpe & Sofka, 2009; van de Vrande et al., 2009).

One issue that remains with the paper, however, is that of survivor bias. While it is clear that, given the lagged structure of our variables, we lose younger firms, we have to admit that the logical opposite also holds true: that we cannot observe firms who would have existed in the period of time for which we begin constructing our independent variables, which, however, went out of business before the survey took place. Analyses we can conduct, such as shortening the time window used to calculate aspiration levels, indicate that this should not be of major concern. However, noting the differences between our sample and all respondents to the UK~IRC survey, it seems that our firms should be slightly better performers than the average start-up. Yet, the difference between the worst performing firms and those we cannot observe because of survivor bias—similar to the logic underlying tests of non-response bias (Armstrong & Overton, 1977)—should be very small. Also, given there is no indication that survivor bias and open innovation should be strongly and directly linked, we believe that survivor bias should not be a major concern with respect to the validity of our results. However, since we cannot observe the open innovation activities on non-surviving firms, we are unable to rule out this potential source of bias.

DISCUSSION AND CONCLUSION

Our study set out to establish a link between the behavioral theory of the firm and open innovation: conceptualizing engagement in open innovation practices as non-local search, we argued, but could not directly find, that such activity should be triggered by the firm under- or overperforming aspiration levels. However, taking a closer look at this relationship, we discovered, in accordance with our hypothesizing, that a direct effect was hidden by moderating factors, most notably human capital and past R&D investment, which substantially affected the relationship between aspiration levels and engagement in open innovation: high-human-capital firms exhibited relatively constant levels of open innovation at all levels of performance, while low-human-capital firms exhibited exactly the behavior predicted by the BTF. And underperforming firms with high R&D investments showed much more pressure to search externally than underperformers with low R&D investment.

Theoretical Implications

Building on these findings, we can make three contributions to literatures on innovation and organization. First, we extend recent attempts at clarifying the emergence of open innovation in industries, which have largely looked at factors external to the firm so far (e.g., Di Minin et al., 2010; Henkel et al., 2013). However, given that we observe firms in the same industry choosing different stances toward openness, we argue that perspectives that account for firm idiosyncrasies need to be increasingly considered. To do so, we conceptualize open innovation as a search for solutions (to problems related to both technology and markets) beyond the boundary of the firm. In turn, our findings highlight differences in search patterns depending on whether the firm has the potential to successfully engage with external actors. Here, both high-human-capital firms as well as underperformers with high past R&D investment show search behaviors that clearly differ from predictions of the BTF. Oppositely, firms that will struggle to look outside depict a search pattern that resembles the predictions made by the BTF more closely. The reasons for this, so we argue, should lie in how these firm-idiosyncratic resource endowments will impact the perceived cost of going open, or the magnitude of importance of doing so. All in all, our results provide evidence that it is the weaker firms that tend to use open innovation more strongly: those with lower human-capital-intensity, lower performing R&D, and less patenting activity. Thus, extending earlier work in this space (van de Vrande et al., 2009), our results provide a first, large-scale evidence that, at least amongst SMEs, necessity rather than opportunity seems to be the core driver of open innovation.

Our second contribution lies in extending our insights with regards to open innovation search to the BTF more broadly. Here, our study makes an important contribution toward improving our understanding of actual search behavior exhibited by firms, in that we directly measure different forms of search activity (e.g., Maggitti et al., 2013), rather than the search process as a whole or its outcomes (see, e.g., Argote & Greve, 2007; Gavetti et al., 2012). In taking this perspective, first, we can show how actual search behavior can be predicted following the logic of the behavioral theory of the firm as long as firm idiosyncrasies are taken into account. In this context, we see how a core facet of our argument also extends considerations of how firms search more generally. In particular, this relates to our finding that high-human capital firms exhibit no difference in using open innovation conditional on performance. Put differently, for such firms, open innovation is no different from local search. We argue that this is because high levels of human capital may represent a permanent conduit through which external knowledge can be continuously accessed. More generally, this would suggest that processes or techniques exist that substantially lower the perceived as well as actual cost of engagement in non-local search activities to a level that they are actually equivalent to local search, and can be engaged in permanently (also see Afuah & Tucci, 2012). Thus, some open innovation practices, similar to information and communication technology (Zammuto et al., 2007), may possibly be regarded as a toolkit using which the organization may in fact be casting *a wider net of local search*. We would call for future research to identify which practices satisfy this criteria, precisely, to understand the conditions under which open innovation is local or non-local search, and derive insights from that for search in the BTF more generally.

Finally, our third contribution lies in our novel, practice-based appreciation of open innovation. Adhering to Chesbrough's definitions (Chesbrough, 2003, 2006), we think that the best way to conceptualize *and* operationalize open innovation is by producing a set of practices that comprehensively covers the activities of most firms that would fall under this definition. From a methodological perspective, this approach also tremendously reduces measurement error, given that no two companies—and as we have shown, possibly even no two researchers—could agree on a precise a priori definition required for precise measurement (e.g., Podsakoff et al., 2003). In this vein, extending earlier work resting on predefined large-scale questionnaires such as the Community Innovation Survey (e.g., Laursen & Salter, 2006; Leiponen & Helfat, 2010), the inventory we present may be considered an useful initial attempt at exhaustively capturing the different forms of open innovation firms may engage in.

Limitations and Suggestions for Future Research

Like any study, ours is also subject to various limitations. We already commented about potential issues of sample selection and survivor bias, and will not repeat them here. In addition, whilst our dependent and independent variables come from different sources of data and are measured at different points in time, we can only assume, but not fully prove, causality.

Moreover, given we are relying on survey data, we have limited insight into the actual cognitions and decisions of managers. While our own exploratory qualitative work seems to lend some additional credibility to our reasoning, we would call for qualitative work to study in-depth the search processes and practices that jointly comprise open innovation, following examples such as work by van Burg and colleagues (2013).

Limitations aside, we think this study is an important step in theorizing the emergence of open innovation. In this vein—and extending the possibilities for future research pointed out above—we hope that future studies will pick up on our observation that weaker firms seem to be more prone to engage in openness, and identify the reasons for that. In addition, we would call for our work to be extended to other contexts—for example, it is quite plausible that cultural factors will influence collaborative behavior, and thus open innovation and search.

Implications for Practice

From the perspective of managers, our results have several implications, three of which seem noteworthy. First, given how we show that firms largely search out of necessity, our study is a call to managers, in particular in SMEs, to reconsider this perspective, in particular in light of the many strategic opportunities engagement in open innovation may create (Alexy et al., 2013a). In this vein, second, we also show how open engagement, if prepared appropriately, may result in search patterns that are virtually indistinguishable from searching within the organization. To be able to so, third, we identify several levers, the most important of which seems to be the level of human capital. In turn, managers, in high-tech as well as low-tech industries, should hire graduates with higher degrees, and when doing so, not only look at their individual skill, but also the knowledge networks which they would allow the firm to access.

TABLES AND FIGURES

Figure 1: Simulation of the Effect of Human Capital

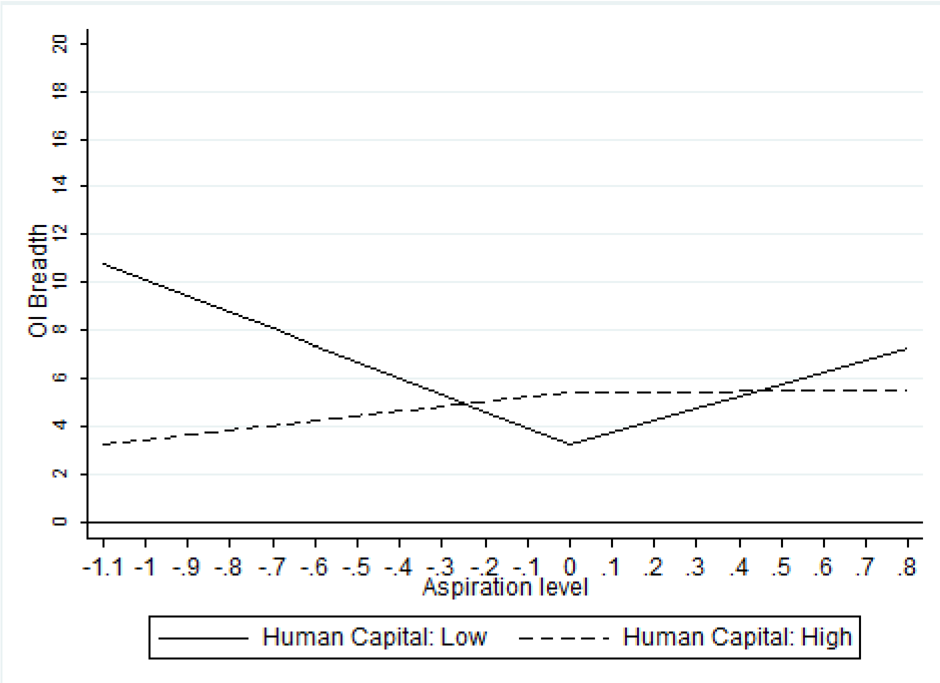

Figure 2: Simulation of the Effect of R&D Investment

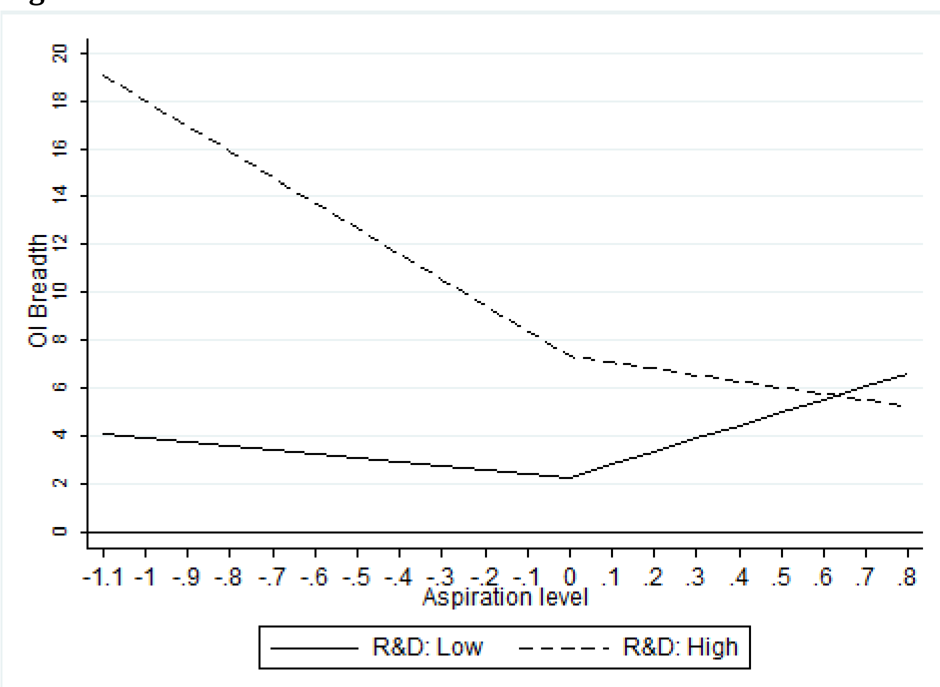

Figure 3: Simulation of the Effect of Patenting Activity

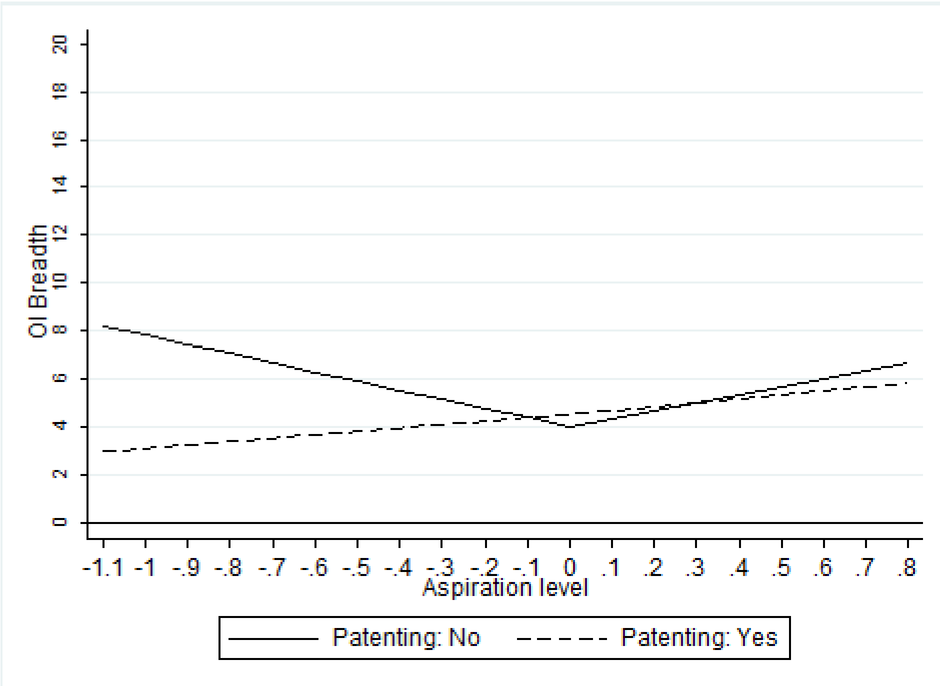

Table 1: Descriptive statistics (N=370)

	(1) OI Breadth	(2) OI Breadth Index	(3) Formal OI	(4) Informal OI	(5) Size	(6) Age	(7) Human Capital	(8) R&D expenditure	(9) Patenting (dummy)	(10) Slack	(11) Inverse Mills Ratio	(12) Below Aspiration	(13) Above Aspiration
(2)	0.94												
(3)	0.95	0.91											
(4)	0.84	0.76	0.63										
(5)	0.24	0.20	0.25	0.17									
(6)	0.03	0.01	0.04	0.01	0.29								
(7)	0.11	0.13	0.09	0.12	-0.31	-0.20							
(8)	0.46	0.44	0.47	0.35	0.43	0.09	0.12						
(9)	0.29	0.27	0.30	0.19	0.20	0.11	0.13	0.40					
(10)	0.04	0.04	0.04	0.02	-0.07	-0.04	0.07	0.09	0.11				
(11)	-0.25	-0.23	-0.25	-0.18	-0.85	-0.04	0.19	-0.44	-0.22	0.02			
(12)	0.11	0.09	0.11	0.09	0.24	0.07	-0.28	0.17	0.10	0.02	-0.28		
(13)	0.09	0.11	0.07	0.10	-0.01	-0.13	0.08	0.14	0.10	-0.02	-0.09	0.31	
Mean	4.28	5.13	2.68	1.60	3.93	2.84	0	0	0.18	0.00	0.36	-0.07	0.07
S.D.	3.85	5.15	2.69	1.53	1.52	0.79	33.59	3.13		10.84	0.12	0.14	0.12
Median	3	3.72	2	1	4.2	2.89	-15.36	0.38	0	-0.97	0.34	-0.012	0
Min	0	0	0	0	0	0.69	-31.34	-3.34	0	-1.73	0.12	-1.11	0
Max	15.00	28.82	10.00	5.00	10.24	4.75	68.66	8.29	1	198.92	0.89	0	0.86

Note: “OI Breadth Index,” “Formal OI,” and “Informal OI” are variations of the dependent variable used in robustness checks.

Table 2: Results of Zero-Inflated Negative Binomial Regressions (N=370)

	Model (1) Baseline	Model (2) Main Effect	Model (3) Interaction HC	Model (4) Interaction R&D	Model (5) Interaction Patents	Model (6) Full Model
Size	-0.011	-0.014	-0.010	-0.024	-0.017	-0.016
	(0.034)	(0.035)	(0.031)	(0.037)	(0.033)	(0.029)
Age	0.001	0.008	-0.003	0.005	0.007	-0.004
	(0.074)	(0.071)	(0.068)	(0.110)	(0.063)	(0.071)
Human Capital (HC)	0.001	0.002	0.005**	0.002	0.001	0.005**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R&D investment	0.110**	0.109**	0.110**	0.120**	0.111**	0.106**
	(0.024)	(0.023)	(0.021)	(0.040)	(0.020)	(0.025)
Patenting (dummy)	0.212**	0.200**	0.188**	0.195*	0.193**	0.176**
	(0.085)	(0.082)	(0.067)	(0.088)	(0.079)	(0.066)
Absorbed Slack	-0.003**	-0.003**	-0.003**	-0.003**	-0.002**	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Underperformance (UP)		0.337	-0.625†	0.452	0.100	-0.568†
		(0.266)	(0.430)	(0.382)	(0.375)	(0.382)
Overperformance (OP)		0.214	0.922†	0.523	0.468	1.097*
		(0.441)	(0.636)	(0.443)	(0.527)	(0.650)
UP * HC			0.025**			0.029**
			(0.007)			(0.009)
OP * HC			-0.023*			-0.019†
			(0.013)			(0.012)
UP * R&D				-0.120		-0.272**
				(0.104)		(0.091)
OP * R&D				-0.301**		-0.217*
				(0.123)		(0.117)
UP * Patenting					0.915*	0.679
					(0.524)	(0.568)
OP * Patenting					-0.620	-0.165
					(0.594)	(0.501)
Constant	**1.602****	**1.613****	**1.564****	**1.659****	**1.611****	**1.617****
	(0.211)	(0.206)	(0.180)	(0.260)	(0.195)	(0.198)
Sector dummies	**Yes****	**Yes****	**Yes****	**Yes****	**Yes****	**Yes****
Chi^2 Value	103.973**	148.858**	268.471**	179.165**	193.483**	310.314**
Log-pseudolikelihood	-890.488	-889.690	-885.923	-885.862	-888.603	-880.856

Notes: Robust standard errors for one-tailed tests clustered by 2-digit SIC code (in parentheses). Sector-level dummies included. † significant at 10%; * significant at 5%; * significant at 1%
Variables used for inflation were firm size, age, perceived competition pressure (number of competitors—here, we experimented with both the true number from the ONS, as well as the perceived number from the survey), sales revenue growth objective (survey), and an industry-level formal IP protection (see Cassiman & Veugelers, 2006).

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APPENDIX

List of Open Innovation Practices Used in the Survey

- Engaging directly with lead users and early adopters
- Participating in open source software development
- Exchanging ideas through submission websites and idea "jams", idea competitions
- Participating in or setting up innovation networks/hubs with other firms
- Sharing facilities with other organisations, inventors, researchers etc.
- Joint R&D
- Joint purchasing of materials or inputs
- Joint production of goods or services
- Joint marketing/co-branding
- Participating in research consortia
- Joint university research
- Licensing in externally developed technologies
- Outsourcing or contracting out R&D projects
- Providing contract research to others
- Joint ventures, acquisitions and incubations