Creativity without walls: The case of open innovation

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Abstract

We investigate the increasingly common practice of open innovation (OI), wherein internal innovation is supplemented with external sources (hackathons, open innovation labs, or crowdsourcing). OI can be value-increasing as it may give access to a larger pool of talent, accelerate idea development, and spread out innovation-related risks. Yet, OI may trigger the revelation of proprietary information and can be hard to integrate. Using a novel dataset, we show that investors view OI initiatives positively. The value-added stems from hiring more productive inventors, boosting incremental innovation, and reducing costs, rather than from growing sales or introducing new products.

Keywords: innovation, open innovation, patents, innovation strategy, firm value.

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1. Introduction

Innovation has long been recognized as a key driver of firm value and competitive advantage (Schumpeter, 1911; Romer, 1990; Porter, 1992). Traditionally, firms tended to rely on internally developed "proprietary" technologies with research and development (R&D) being completely integrated within the boundaries of the firm (i.e., closed innovation). Recently, a new paradigm emerged (i.e., open innovation), which runs counter to the secrecy and silo mentality of traditional corporate research labs and suggests that firms could instead explore a wide range of internal and external sources for innovative opportunities (Chesbrough, 2003). For example, a firm can widely broadcast an internal problem and invite parties external to the firm to offer solutions via tournaments, hackathons, or crowdsourcing.[1] In this paper, we provide the first large-sample evidence on factors that predict open innovation (OI) and explore the implications of adopting the OI paradigm on corporate performance.

OI can give firms access to a broad pool of diverse ideas, talents, and technology, as well as reduce risks associated with innovation by spreading it across different parties. OI can break down traditional silos between industries, provide shared access to cutting-edge technologies, and facilitate partnerships among diverse participants. These collaborations can accelerate problem-solving and innovation by leveraging participants' unique perspectives and combining complementary skills. Hence, OI can create economic value for companies (e.g., Chesbrough, 2003; Laursen and Salter, 2006; Leiponen and Helfat, 2010). However, opening up to external sources can increase the danger of revealing critical knowledge to outsiders, which may lead to the loss of competitive advantage, weaken the firm's ability to reap returns from collaboration, and entail substantial risks of appropriation and opportunism (Hennart, 1988). Furthermore, external ideas can rarely be plugged straight into the existing knowledge, and cultural factors can make it difficult to integrate ideas that were "not invented here." The increased coordination costs and

[1] Examples of open innovation initiatives include: i) Philip's open innovation lab called MiPlaza, where companies can develop their own applications with access to Philips research and know-how. In return, Philips can use the inventions made by companies in the lab to improve their own solutions; ii) Samsung Accelerator program, which brings together entrepreneurs, designers, innovators, and experts, and offers them office spaces, capital, and product support to yield exciting new solutions; and iii) Microsoft created its new Microsoft for Startups program to connect its technological platform and marketing skills with the creativity of startups.

intellectual property risks associated with OI might prevent firms from realizing synergies from external collaborations and render OI value-decreasing. Indeed, in a recent poll by Accenture, more than 50% of the corporations surveyed said that OI partnerships did not seem to be yielding as many benefits as they had hoped.

We start our analysis by examining the prevalence of OI initiatives and the factors that predict such engagements. Using a novel dataset that relies on data derived from LinkedIn job descriptions and news articles that feature OI engagements, we construct two measures of OI: i) the annual percentage of OI jobs at each firm, which captures firms' human capital investment in OI,[2] and ii) annual # of OI headlines. Both measures show that the incidence of OI has increased dramatically over time. For instance, the number of firms with at least one OI position (headline) has grown from 720 (179) in 2001 to 1,168 (1,272) in 2020. The share of OI positions (headlines) is highest in the computers, software and equipment industry, i.e., 51% (19%), and is the lowest in utilities, i.e., 19% (8%). At the firm level, we find that firms engaging in OI are generally larger. Firms with higher R&D are also more likely to initiate OI, suggesting that OI is a complement, rather than a substitute, to internal R&D capabilities. Similarly, firms with OI are more likely to engage in other external collaborations, such as joint ventures and alliances. Firms appear to prefer internal funds for financing OI, as we observe that firms with OI have higher cash reserves and lower leverage. We do not find that firm performance predicts the propensity to engage in OI.

We then proceed to analyze the value implications of engaging in OI, by estimating investors' response to news announcing OI initiatives. A major advantage of analyzing announcement returns is that they are less likely to be driven by reverse causality or omitted firm or CEO characteristics (Kai and Prabhala, 2007). We find that investors respond positively to OI initiatives, though the market response is modest. For instance, the three-day median CAR is 0.053% ($p<0.01$). The market response is more pronounced in firms for which first-mover advantage and faster innovation afforded by OI are critical, such

[2] Some examples of OI jobs include: i) "Developing and implementing open innovation strategy"; ii) "Established company's first open innovation hub"; iii) "Provides comprehensive support to attorneys in the Open Innovation Counseling Team on complex legal matters". More examples are available in Appendix A.

as those operating in high-tech industries, and for firms operating in states where it is easier to attract talent, such as those with weaker enforcement of non-compete agreements.

We consider four potential not mutually exclusive channels through which OI may benefit firms: i) better access to human capital; ii) increased innovation; iii) decreased operating costs; and iv) growth in sales.

According to the first channel, OI may help firms recruit more talented employees, by reducing information asymmetry about potential employees' abilities and their fit with the firm that is inherent in the recruiting process. For instance, General Electric uses open innovation for this purpose via its GeniusLink Challenges, where people can submit their solutions and win prizes, some of which entail internships. This selective process helps GE find the most talented individuals with whom they can later engage via job opportunities or paid internships. To test whether OI allows firms better access to human capital, we study the effects of OI on individual inventors' mobility. We focus on inventors because: i) they are major contributors to the overall human capital within the firm; ii) we can track their employment history using patent filing data, and iii) we can measure their productivity. Our analysis of inventors' relocations, however, can, at least partially, generalize across many different types of employees.

Our results suggest that the adoption of OI triggers changes in the composition of the inventor base. We find that firms with OI engagements experience a significant inflow of inventors. Although we also document a significant outflow of inventors in firms with OI, the net inflow of inventors is positive. When we compare the productivity of departing inventors and new hires, we find that the newly hired inventors are more productive compared to leavers in terms of both patents filed and citations per patent.

To provide further evidence on this channel, we analyze the changes in inventor flow around the introduction of GitHub, which is the largest collaborative online platform. GitHub has made it easier for firms to engage in OI and access skilled labor. GitHub allows companies to quickly search for potential candidates with relevant expertise and observe candidates' skills "in action" by providing access to candidates' actual code and real-world projects they contributed. Using a differences-in-differences estimation, we compare the change in net inventor inflow following GitHub introduction (our proxy for a positive shock to OI adoption) for firms that did not engage in OI prior to GitHub (i.e., treated firms) to those that had already engaged in OI before GitHub introduction (control firms). We find that treated firms significantly increased the net inflow of inventors following the introduction of GitHub relative to the set of controls, providing support to the idea that an improvement in the ability to conduct OI is associated with a greater inflow of talent.

We also verify that the positive relation between OI engagements and inventor flow is robust to the inclusion of firm fixed effects and a rich set of time-varying firm characteristics. This result also holds if we include industry-year and state-year fixed effects, use alternative regression models, or rely on a shift-share/Bartik instrument. However, we acknowledge that a consistent positive relation between OI and inventor inflow we document is one of association and not causation.

According to the second channel, OI may increase firm value by stimulating corporate innovation either by boosting the productivity of the existing ones or by attracting more productive inventors. To examine this channel, we analyze the relation between the OI engagements and the number of patents. We find that firms with OI engagements file more patent applications in the future. Furthermore, our OI metrics are also positively related to patent quality, as measured by citations and patents' economic value. We next explore the relation between OI engagements and the direction of innovation strategy, by asking whether OI enhances firms' exploration capabilities that could lead to breakthroughs or whether it fosters exploitative, incremental innovation. Prior work has emphasized that the diversity of knowledge is particularly important for the development of radical innovations. Therefore, the diversity of stakeholders involved in OI may lead to more creative, out-of-the-box solutions. Yet, more radical innovations might face higher resistance to be adopted and might be harder to integrate. Furthermore, OI participants may hesitate to share their most valuable insights, fearing that others might exploit their ideas without proper recognition or compensation. Indeed, our analysis shows that OI benefits firms by improving their exploitative capabilities rather than helping them uncover breakthrough projects. Furthermore, firms with OI are more likely to focus on process, rather than product, innovation, which further points to an exploitation strategy. We also observe that firms with OI innovate more efficiently, as evidenced by a higher number of patents per dollar of R&D.

Our third channel suggests that OI might improve operating efficiency because it enables firms to exploit other organizations' discoveries, i.e., may help firms find solutions faster and/or lessen the costs of developing new products (Chesbrough and Crowther, 2006). We note that this channel is separate from the first two channels, as not all patents/new hires lead to cost reductions and not all OI engagements result in patents/new hires. To examine the cost savings channel, we analyze the relationship between OI engagements and two broad measures of operating efficiency: total factor productivity and the cost of goods sold. Our analysis shows an increase in total factor productivity, suggesting that these firms convert their investments into output more efficiently. We also find weak evidence of lower costs of goods sold for firms with OI engagements.

Lastly, we examine whether firms use OI as a marketing ploy to grow sales. For instance, OI might help increase publicity of firms' products, facilitate the creation of new products, or better tailor products to customer tastes. To explore this channel, we analyze the relationship between OI, sales growth and the introduction of new products. Empirically, we do not find support for this channel, as OI engagements are not associated with sales growth or the introduction of new products. These results suggest that firms use OI mostly to acquire talent and develop new technology that can reduce costs rather than for sales growth. These results contrast with the survey evidence that offensive reasons (stimulating growth) are more important than defensive reasons (decreasing costs and risks) (Chesbrough and Crowther, 2006; Van De Vrande, Jong, Vanhaverbeke, De Rochemont, 2009).[3]

In light of our findings suggesting that firms benefit from OI, a natural question that arises is why some firms choose to *not* engage in OI. Some reasons why firms might prefer in-house innovation include: i) it might be easier to build on internal, rather than external, technologies because the originators of in-

[3] For instance, Chesbrough and Crowther (2006) found that cost reduction was a "secondary" motivation, while a survey of firms of 10–500 employees found that cost reduction was a less frequent goal, compared with improving innovation outputs, gaining external knowledge, or tracking changes in market demands (Van de Vrande et al., 2009)

house technologies likely remain in-house and can provide comprehensive and tacit nuance regarding these technologies; ii) formulating problems suitable for outside solving might not be feasible; iii) legal requirements of transferring intellectual property can become roadblocks for collaboration; iv) integrating OI may pose challenges about how to change the culture inside the company, as OI might require not just adopting new collaboration tools but also change the way companies work; and v) organizations might favor the use of their in-house technologies over those of external sources, even if doing so may be suboptimal (Cyert and March, 1963; Katz and Allen, 1982; Sørensen and Stuart, 2000). These and other possible considerations likely lead to an equilibrium in which some, but not all, companies choose to engage in OI.

Our paper is related to a broad financial economics literature on innovation, as surveyed by He and Tian (2017). Unlike many papers in finance that examine the relations between innovation and various firm- and CEO-level characteristics, this paper takes a deeper look into *how* companies engage in innovation. In this respect, our paper is related to studies in business strategy and management, which have investigated open innovation topics, but mostly concerned theoretical debates based on case studies, single industries, and small samples, limiting the generalizability of their findings.[4] We extend this literature along several important dimensions.

First, our paper uses the first large-scale dataset that examines a broad range of OI covering multiple industries over a longer period, which allows us to provide a more complete picture of this growing phenomenon and add new insights about when external knowledge is most valuable. Second, whereas prior studies mostly rely on surveys and in-depth interviews to capture the instances of OI, we introduce two novel measures of firm-level engagement in OI that allow us to: i) provide the first evidence of the investor

[4] The heterogeneity in the characteristics of the samples and various approaches used to measure innovation performance resulted in a lack of agreement on the effect of OI on innovation performance. For instance, some authors found a positive, sometimes curvilinear, relationship between OI and innovation performance (e.g., Laursen and Salter, 2006; Asakawa, Nakamura, and Sawada, 2010; Grimpe and Kaiser, 2010), while others found no relation, or even negative relationship (e.g. Campbell and Cooper, 1999; Lhuillery and Pfister, 2009; Un, Cuervo-Cazurra, Asakawa, 2010; Lifshitz-Assaf, Lebovitz, and Zalmanson, 2021; Dahlander and Gann, 2010; Faems, Visser, Andries, van Looy, 2010).

response to OI announcements, and ii) capture firms' actual investment in OI-skilled human capital. Third, whereas prior literature mostly focused on the relation between OI and innovation, we identify two important new channels, i.e., access to labor capital and improvement in operating efficiency, that link OI engagements to increases in firm value. Lastly, whereas prior studies predominantly used the introduction of new products to quantify the relation between OI and innovation,[5] we focus on firms' patenting activity, which allows us to assemble a suite of more detailed and nuanced measures of innovation. Studying patents also enables a cleaner identification of a firm's innovation search strategy, thereby offering new evidence not only about the rate but also about the type and direction of innovation. Our results highlight that OI enhances firms' exploitation, rather than exploration, innovation strategy, suggesting that firms are likely to use OI in the later stages of the product life cycle.

Our paper is also related to a new and growing literature in finance showing that firm boundaries matter for innovation and that acquiring innovation from external sources has become an important component of corporate innovation. For instance, Seru (2014) shows that firms acquired in diversifying mergers produce fewer and less novel patents afterward and that this is driven by a decline in inventors' productivity rather than inventor exits. Bena and Li (2014) show that innovative firms are more likely to be acquirers and that bidders with higher technological overlap with their target firms produce more patents afterward. In contrast, Ma (2020) shows that firms with deteriorating internal innovation are more likely to use corporate venture capital to invest in entrepreneurial companies with proximate but new technologies to fix innovation weaknesses. In our setting, innovation is sourced via arms' length transactions in the marketplace, rather than hierarchical transactions within the firm (e.g., acquiring the innovation partner) or hybrid forms of organization (e.g., strategic alliances, joint ventures). Our results highlight a novel and increasingly important approach to sourcing new ideas that firms can use to boost their innovation and firm value.

[5] E.g., Boudreau (2010), Laursen and Salter (2006), Grimpe and Sofka (2009), Frenz and Letto-Gillies (2009).

2. Data and descriptive statistics

2.1. Sample

Our sample includes all firms at the intersection of Compustat and LinkedIn datasets from 2001 to 2020. We obtain annual accounting information from Compustat and stock return data from CRSP. We identify the characteristics of the CEOs using data from BoardEx. We collect data on alliances, research collaborations, and joint venture relationships for the firms in our sample from FactSet Revere. The data availability requirements led to a final sample of 30,413 firm-year observations for 3,917 firms. We present the descriptive statistics of firm characteristics in Table 1. The median firm in our sample has book assets of $972 million, a market-to-book ratio of 1.6, and a ROA of 12%.

2.2. Defining and measuring open innovation

Unlike a closed approach to innovation, which entails the complete integration of R&D within the boundaries of the firm, open innovation involves a systematic exploration of a wide range of external knowledge sources (i.e., customers, rivals, suppliers, experts, and crowds) for innovation opportunities and integrating that exploration into a firm's innovative processes (Cohen and Levinthal, 1990; Chesbrough, 2003).

Some examples of open innovation include: i) *challenges and contests*, which are competitions aimed at engaging external, professional stakeholders to accomplish a specific goal. For instance, in 2006, Netflix launched an open innovation challenge called Netflix Prize that was open to anyone from the public. The competition intended to find a filtering algorithm that improves user movie or series suggestions by 10% compared to the existing one. For the winner of the competition, Netflix offered a grand prize of 1 million USD. In just over a year, over 40,000 teams from 186 countries entered the competition. Although the tournament allowed Netflix to pick a feasible algorithm that improved the suggestions by 8.43%, it also raised user privacy concerns as it had to release user data so that applicants could test their algorithms. On a positive note, Netflix was able to find talented programmers and market their product and new suggestion feature.[6]ii) *crowdsourcing*, which refers to the publishing of an open call, typically enabled by digital platforms, to a large, undefined crowd to solicit ideas, feedback, and content so that many different actors can contribute to solving a complex task. In 2009 Mountain Dew released a platform named DEWmocracy where customers were able to develop new lemonade flavors together. Although the venture was a huge success initially, it fell victim to misuse and hacking. Mountain Dew received significant PR backlash, which led to the demise of the site and the contest; iii) *hackathons*, which are accelerated innovation processes that bring together individuals to solve specific and ambitious challenges in an extremely limited and ad hoc time frame (72 hours or, in some cases, less). For instance, in 2015 Capital One hosted a public hackathon where 177 developers spent the weekend hacking to create apps that engage millennials on mobile and help cool consumers' fear of personal finance. Participants were offered three cash prizes from $5k to $12k. Developers were also able to retain ownership of their code while Capital One could access and use all ideas generated; and iv) *open innovation labs* and *accelerators*, which provide collaborative, development-focused ecosystems where external partners such as startups, suppliers, innovators, and experts work with internal teams from an organization to address corporate challenges and opportunities. For instance, Liberty Mutual opened an innovation hub called Solaris Labs to build and test new products based on emerging trends and customer research.

To identify the instances of OI, we use a conservative approach and rely on a narrow set of words that are directly related to the examples of open innovation described above. Specifically, we use the following keywords: "open innovation", "hackathon", "crowdsourcing", "innovation contest", "open center", "innovation lab", "accelerator", "tournament", "open R&D", "open platform," and "external technology sourcing". We acknowledge that our method may not fully capture all relevant OI engagements and potentially overlooks some OI initiatives. However, we note that our results are robust if we use a broader set of keywords.[7] Relatedly, we do not include alliances, joint ventures, corporate venture capital,

[6] https://www.viima.com/blog/open-innovation
[7] For instance, if we use a more comprehensive list of keywords, which includes "external innovation", "collaborative innovation", "knowledge sharing", "sourcing innovation", "intellectual cooperation", "innovation licensing", "open source", "in-licensing", and "technology licensing."

or acquisitions of the innovation partner, as these arrangements often entail formal agreements between firms, imply a specific legal basis (a contract), an objective (R&D), and a type of partner (firms) and differ from typical OI initiatives in terms of the level of resource commitment, number of actors, flexibility, focus, and duration. Additionally, we focus on inbound OI, wherein knowledge and resources flow into firms, and exclude outbound OI, wherein firms export their knowledge and resources (e.g., via outbound licensing, the provision of the R&D contracting, or publicly disclosing their innovations).

We construct our first measure of OI using detailed data on position descriptions from LinkedIn. We note that although LinkedIn started in 2003, it contains a retrospective work history, which enables us to construct our measure for the period before 2003. To identify employees engaging in OI, we search for job titles and job descriptions for the above OI keywords. We clean the data obtained from this initial search, by reviewing job descriptions and titles to make sure that: i) the person in question is engaged in an open innovation and ii) has been employed by the focal company. For instance, a person listing “Third Place Best Hackathon Overall App (AT&T Mobile App Hackathon), 2012” but not working for AT&T would not be considered an AT&T employee. We consider a firm-year observation to contain an OI job if the fiscal year end falls within the starting and end dates of the OI job. Appendix A provides examples of such job descriptions. Our second measure relies on news articles from RavenPack Analytics search. Specifically, we search for news containing the company name and any of our OI keywords. We clean the data by: i) removing duplicate news, keeping the earliest one, and ii) reviewing articles to ensure that the news article captures an instance of open innovation initiative. Appendix A provides examples of such news articles.

Figure 1 presents the trend in using OI among our sample firms and shows that the number of firms with at least one OI position (headline) has grown from 720 (179) in 2001 to 1,168 (1,272) in 2020. Panel A of Table 2 reports the proportion of OI headlines and jobs by industry. Firms operating in fast-changing industries, such as computers and electronic equipment and telephone and television transmission, have a higher incidence of OI headlines with 18.6% and 17.0%, respectively. In contrast, firms in utilities engage in OI less frequently, i.e., only 7.7%. The distribution of OI positions across industries is similar. Panel B of Table 2 presents the annual distribution of OI positions and headlines: 24% of firm-year observations have between 1 and 5 OI positions, 3% have between 6 and 10 OI positions, and about 5% of firm-year observations have more than 10 OI positions. The distribution of annual headlines is similar with 9% of firm-year observations having between 1 and 5 OI headlines and 3% having more than 10 headlines per year.

3. Determinants

This section examines which ex-ante firm characteristics predict engagement in OI initiatives. We start by considering several fundamental firm characteristics. Given that firm size is an important determinant of firms' innovation output and strategy (e.g., Huergo and Jaumandreu, 2004; Bernstein, 2015), we conjecture that size may also determine the decision to engage in OI. However, the direction of the effect is unclear ex-ante. Small companies can gain a lot by open innovation as both their resources and market reach are limited. However, they also have fewer resources to create and enforce intellectual property rights and build and maintain collaborative networks, which can prevent them from engaging in OI. In contrast, larger firms might be better positioned to undertake collaborative relationships and enforce intellectual property rights yet might be more likely to exhibit "not invented here" syndrome, i.e., resistance to ideas originating outside the organization.

Another important company characteristic that can determine OI is the level of internal R&D intensity. Prior literature has argued that the extent to which a firm can screen, value, and utilize knowledge that originates from beyond its boundaries depends on its absorptive capacity, i.e., firms need prior related knowledge to access and assimilate external knowledge that is absorbed (Cohen and Levinthal, 1990). Consistent with this, Bena and Li (2014) show that firms with stronger internal innovation are more willing to expand firm boundaries to harvest innovation synergies. Hence, higher R&D spending might be associated with greater use of OI, as firms with higher R&D might be better at assimilating and commercializing external knowledge. However, higher R&D intensity might also reduce the need for collaborations, as firms with high levels of confidence in their R&D competencies might also be less interested in external technology and might tend to use internal innovations. This suggests that the relationship between R&D and OI will be negative, as these firms might be more rigid in adopting external ideas. We proxy for internal innovation capabilities by R&D expense and a missing R&D indicator.

We also examine whether the investments in OI are complements or substitutes to alternative investments in external collaborations, such as alliances, research collaborations, and joint ventures. To this end, we include a dummy that equals one if a firm has at least one joint venture/alliance, and zero otherwise. Prior studies also suggest that internal funds and capital structure can impact the amount and nature of innovation undertaken by firms (Hall and Lerner, 2010; Kerr and Nanda, 2015; Himmelberg and Petersen, 1994). To explore how the availability of financing affects firms' OI investments, we include cash and leverage to capture internal and external financing. We also add several other firm characteristics, such as ROA, cash, asset tangibility, leverage, capex, M/B, and firm age. We include industry competition, as industry composition can be an important factor in determining firms' resource dependence, transaction costs, and, therefore, innovation choices.

Given that the OI adoption may require changes in corporate culture and the establishment of new innovation processes, we conjecture that CEOs who are hired externally will be more likely to engage in OI. Similarly, we conjecture that younger CEOs and CEOs with more power might be more likely to engage in OI. Hence, we include outside CEO dummy, CEO age, and CEO/Chair duality. We also include 3-digit SIC industry dummies and year fixed effects to capture time trends and differences across industries. We cluster standard errors at the firm level to account for multiple observations per firm. Control variables are measured at the prior year-end. All variable definitions are in Appendix B.

Columns 1 and 2 of Table 3 present estimates from a regression model, in which the dependent variables are the natural logarithm of the annual count of unique OI positions, scaled by the total number of employees and the annual count of unique news articles that capture OI engagements, respectively. We find that R&D expense is positively related to OI, suggesting that OI is a complement, rather than a substitute, for internal innovation. This is consistent with the argument that firms with more absorptive capacity are more likely to gain knowledge outside their firm boundaries (Cohen and Levinthal 1990; Dushnitsky and Lenox 2005; Ma, 2019). Similarly, our results show a positive relation between OI and alliances/joint ventures, suggesting that OI is a complement to these alternative methods of sourcing knowledge externally. We also document that firm size and market-to-book ratio are positively associated with OI. Furthermore, we document a positive coefficient on cash holdings and a negative coefficient on leverage, suggesting that firms are more likely to experiment with OI when they have greater internal financial resources. We note that prior performance does not play a role in explaining the adoption of OI. Among observable CEO characteristics, we find that firms with younger CEOs are more likely to undertake OI initiatives. In Columns 3 and 4, we replace industry fixed effects with firm fixed effects and observe that the only robust predictor that explains within-firm OI variation is engagement in alliances/joint ventures.

4. OI and firm value

The proponents of open innovation argue that OI may be value-increasing as it enables firms to access new and valuable resources from external actors. By pooling knowledge and fostering cross-pollination of ideas, OI can foster new idea creations and speed up idea development. OI can also spread out the financial and technical risks associated with innovation and provide shared access to cutting-edge technologies and infrastructure (Chesbrough, 2003; Laursen and Salter, 2006; Leiponen and Helfat, 2010). On the other hand, pushing problems out to a vast group of strangers may seem risky and even unnatural, particularly to organizations built on internal innovation. Transaction cost economics suggests that external collaborations are often subject to high opportunism and knowledge spillover risks, which can expose the firm's core competencies to rivals (Hennart, 1988). With multiple stakeholders contributing ideas and resources, disputes over ownership of intellectual property can arise, which can restrict the firm's ability to fully appropriate the returns from collaborations. Furthermore, organizing innovative activity across the firm boundary increases the difficulty of coordination, communications, and knowledge integration (Grant, 1996). To examine whether the benefits of OI outweigh the costs, we analyze announcement returns surrounding OI initiatives identified from the news articles.

4.1. OI announcement returns

We compute cumulative abnormal returns (CARs) by employing a standard market-adjusted return model, where the abnormal return is calculated as the difference between a firm's return and the value-weighted market (CRSP) index return. We calculate cumulative abnormal returns over two- [-1:0], three- [-1:+1], and four-day [-3:0] windows, with time $t = 0$ being the OI announcement date.

Panel A of Table 4 presents the announcement returns over the different event windows. We observe positive and statistically significant mean and median announcement returns to OI engagements across all windows. The mean two- and three-day CARs are 0.081% ($p < 0.01$) and 0.100% ($p < 0.01$), respectively, whereas the median two- and three-day CARs are 0.040% ($p < 0.01$) and 0.053% ($p < 0.01$), respectively. These results show that OI engagements are associated with a modest, but positive market response.

A potential concern that one might have is that our estimates of investors' reactions to OI might be contaminated by reactions to other news. To examine this possibility, we conduct two placebo tests, in which: a) we generate random dates for the sample firms and examine market reactions around these placebo dates, and b) we analyze market reactions to "false" OI engagements, i.e., news that contain keywords from our list but that do not represent OI initiatives. In both cases, we observe that placebo tests yield no significant effects, confirming that our announcement returns results are picking up investor reactions to OI rather than a market reaction to any news. Our results are also robust if we omit OI engagements that are potentially contaminated by other confounding events, such as dividend payments, dividend announcements, merger announcements, or earnings restatements that occur within +/- 5 days of the OI engagements (untabulated).

4.2. Cross-sectional variation

We now turn to examine whether the market reaction varies by: i) the nature of the company's business; ii) industry competition, and iii) the enforcement of non-compete agreements.

A vast body of research suggests that innovation work and new product development processes take time (Brown and Eisenhardt, 1995; Garud, Gehman, and Kumaraswamy, 2011). The proponents of OI have suggested that an open approach can accelerate the innovation process and reduce the time to market (Chesbrough, 2006). If OI enables performing some innovation activities significantly faster, then it might be more beneficial for firms operating in environments characterized by rapid technological change. We test this conjecture in Panel B of Table 4 by splitting the sample into firms that operate in high-tech industries[8] and those that do not. We observe that although the market reaction is positive in both sub-samples, the magnitudes are larger for firms operating in the high-tech industry (p-value < 0.1 or less for the difference in coefficients). This evidence is consistent with our conjecture that OI is more valued when firms operate in faster-paced industries.

Next, we examine whether the value of external innovation varies with industry competitiveness. Product market competition increases a firm's pressure to keep competitive advantages over its rivals and generate profits in the short run to satisfy its equity market investors (Aghion, Van Reenan, and Zingales, 2013). Furthermore, in such industries the efficient deployment of resources and the first-mover advantage becomes critical. If the companies that can innovate faster are more likely to gain a competitive advantage, we expect that the positive effect of OI on innovation to be more pronounced when the firm is operating in a more competitive product market. On the other hand, the potential leakages of information associated with OI engagements can be especially detrimental in more competitive industries, suggesting a negative effect of OI in such industries. We test these cross-sectional conjectures by splitting the sample based on the median value of the HHI, which is calculated by summing the square of each firm's market share (in sales) at the 4-digit SIC level. Panel C of Table 4 reports CARs for firms operating in more (less)

[8] We define a sample firm as high-tech if it operates in one of the following SIC codes: 3571-3572, 3575, 3577, 3578, 3661, 3663, 3669, 3674, 3812, 3823, 3825-3827, 3829, 3841, 3845, 4812-4813, 4899, 7370-7375, 7378-7379.

competitive product markets. Our results do not show significant differences between firms operating in more and less competitive industries.

Last, we examine whether the market response is moderated by labor mobility. We conjecture that firms operating in environments wherein it is easier to hire the participants of OI initiatives might benefit more from OI. To gauge variation in labor mobility, we create an annual state-level index that captures the degree to which state courts enforce covenants not to compete. Panel D of Table 4 reports CARs for firms operating in more (less) mobile labor markets. We find that market response is higher for firms located in more mobile labor markets, suggesting that the benefits of OI are more likely to materialize when firms can recruit qualified workers with relevant experience.

5. Channels

In this section, we examine four non-mutually exclusive channels that can link OI to value creation. Specifically, we analyze the relation between OI and human capital access (Section 5.1.), innovation (Section 5.2.), cost efficiency (Section 5.3.), and sales growth (Section 5.4.).

5.1. Human capital access

Companies typically face the problem of not being able to perfectly observe the quality of prospective employees. OI can potentially help overcome this issue as it can allow firms to assess prospective employees' abilities and assess their potential fit with the firm before making the hiring decision. Hence, firms with OI can find and engage individuals that are perfect for the existing job opportunities, instead of selecting a "close enough" fit from inside the company. To explore this idea, we examine the relation between OI engagements and a firm's ability to attract a particularly important subset of employees, i.e., inventors.

5.1.1. Baseline result

To identify inventor flow, we rely on the patent datasets of Kogan, Papanikolaou, Seru, and Stoffman (2017) and Stoffman, Woeppel, and Yavuz (2022)[9] and assume that an inventor's job change occurs at the midpoint between the two patent application years (Marx, Strumsky, and Fleming 2009; Hombert and Matray, 2017; Li and Wang, 2022). For instance, if an inventor applies for a patent with firm A in 2015 and their next patent with firm B in 2019, we assume the job change occurs in 2017. We define an inventor as a new hire for firm B in 2017 and as a leaver for firm A in the same year.[10]

In Panel A of Table 5, the dependent variable is the number of inventors joining the firm at t+1 (Columns 1 and 4), t+2 (Columns 2 and 5), and t+3 (Columns 3 and 6). Our regression models include the same set of time-variant firm characteristics as used in our earlier analysis of the determinants of OI. In addition, we include year fixed effects and firm fixed effects to control for any unobserved time-invariant firm heterogeneity. We cluster standard errors by the firm. To reduce skewness in the number of inventors, we apply the inverse hyperbolic sine transformation to the dependent variable, which allows us to accommodate the frequent occurrence of zero values in our sample. The IHS transformation approximates the natural logarithm function but is considered superior to the shifted log transformation because it handles

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[9] See Noah Stoffman's website at https://kelley.iu.edu/nstoffma/ and Michael Woeppel's website at https://www.mikewoeppel.com/data.

[10] We also use an alternative approach to measuring the timing of the inventor relocations. Specifically, following Gao and Zhang (2017), we define an inventor as a new hire for firm i in year t if she files for her first patent in firm i in year t after filing a patent in a different firm in a previous year. We define an inventor as a leaver for firm i in year t if she previously filed patents for firm i but starts to file patents for another firm in year t. For instance, if an inventor applies for a patent with firm A in 2015 and for another patent with firm B in 2019, the job change is considered to have occurred in 2019. We define an inventor as a new hire for firm B in 2019 and a leaver for firm A in that same year. Our results are robust to this alternative approach (untabulated). As an additional robustness check, we re-estimate our regressions by restricting our measures of inventor flows to include only inventors who have moved between firms within a 1-year (3-year) window, e.g., an inventor applied for a patent at firm A in 2018 (2016) and for another patent with firm B in 2019. Doing so narrows the time-period during which a job change has occurred and improves our ability to capture the timing of inventor flows more accurately. Our results remain similar using these metrics (untabulated).

zero and negative values without needing to arbitrarily shift the data. It also provides a smoother transition between zero and positive values, maintaining a consistent rate of transformation across all values.

Our variable of interest in Columns 1-3 is *% of OI positions,* which is an annual count of OI positions, scaled by the number of employees and in Columns 4-6 is *# of OI headlines*, which is an annual count of OI headlines. Our results are robust if we scale the *# of OI headlines* by the total annual number of headlines. We observe that the coefficients on both OI measures are positive and significant, suggesting that OI engagements help firms attract inventors. For large values, the HIS transformation approximates the logarithm of the variable. Under this setup, the economic interpretation of the regression coefficients reflects elasticity. For instance, the coefficient on the *% of OI positions* in Column 1 suggests that a 10% increase in OI positions corresponds to an approximately 0.45% increase in the number of new inventor hires.

In Panel B, we examine the relation between OI and inventor exits. Although OI might help attract new talented inventors, it can also reduce incumbent inventors' incentives to innovate within the existing firm and might be associated with a higher rate of departures, as some inventors might feel less valued by their firms. Firms might also decide to let go of some of their existing inventors if they replace them with new ones. The dependent variable in Panel B is the annual number of inventors leaving the firm. We observe that firms with OI engagements experience greater outflows of inventors. Based on the coefficient in Column 1, a 10% increase in OI positions corresponds to about a 0.64% change in the number of leavers. In Panel C, we examine the association between OI and net inventor flow, by using the difference between the number of new hires and the number of leavers as the dependent variable. We find a significantly positive coefficient on the OI metrics, suggesting that newly hired inventors outnumber the leaving inventors.

We next compare the productivity of newly hired inventors and leaving inventors. To estimate the productivity of each inventor, we follow Gao and Zhang (2017) and track patents filed by each inventor and the patent citations received by these patents over our sample period. Following the existing innovation literature, we adjust these measures to address possible truncation problems (Hall, Jaffe, and Trajtenberg, 2001; 2005).[11] We then construct two new measures: i) net patents, which is the difference between the number of patents generated by the newly hired inventors and the number of patents generated by the leaving inventors; and ii) net citations, which is the difference between the total number of citations generated by the newly hired inventors and the number of citations generated by the leaving inventors. These variables intend to capture whether the newly hired inventors are more productive than the leaving inventors, thereby signaling a value-added inventor reshuffling. We use net patents and net citations as dependent variables in Panels A and B of Table 6, respectively. We observe that newly hired inventors compare favorably to leaving inventors, as the coefficients on OI measures are positive. These findings suggest that OI engagements enable firms to attract more productive inventors.

5.1.2. GitHub introduction

To provide further evidence on the labor market channel, we rely on the introduction of GitHub, which is the largest collaborative software development platform that allows software developers to share code and collaborate with other developers on open-source projects in real-time. GitHub was launched in April 2008 and has expanded exponentially in the past decade.[12] As more developers and inventors joined GitHub, it became the default platform for open-source projects with a diverse pool of talent.

GitHub has significantly increased the ease of engaging in OI because it provides a set of project collaboration features that allow firms to engage participants from outside firm boundaries. GitHub has also made it easier for companies to identify talent because GitHub's user profiles serve as up-to-date, living portfolios that showcase candidates' real-world contributions. GitHub allows companies to quickly search for candidates based on a variety of criteria (e.g., programming language, location, skills, or specific

[11] To account for the lag in patent approval, we adjust the number of patents by first estimating the distribution of the application-grant lag, based on the data from 2010 to 2015, and then by computing the truncation-adjusted patent counts for the period from 2016 to 2019, based on the estimated distribution. To take into account that the patents created near the end of the sample period have less time to accumulate citations, we scale the citation count of each patent by the average citation count received by all patents granted in the same year and same CPC patent class.

[12] While there are certainly many projects that are not on GitHub, GitHub has significantly more projects and contributors than other services such as SourceForge or Bitbucket. In 2024, GitHub hosted over 420 million software projects (repositories) and included over 100 million developers and more than four million organizations (including 90% of Fortune 100 companies). Based on github.com/about

projects they contributed to) and assess the quality of a candidate's actual code and technical abilities. Furthermore, GitHub can help identify passive candidates who may not be actively seeking new opportunities but are open to the right offer. As of June 2021, GitHub has generated more than 5.09% of the referral traffic to LinkedIn, making it the second leading traffic source to LinkedIn. Some examples of companies using GitHub to identify talent include: i) Netflix relies on GitHub to find candidates for a variety of positions, including software engineers, data scientists and product managers; ii) Facebook uses GitHub to find candidates for its engineering and product teams by identifying people who contributed to popular open-source projects; iii) Airbnb uses GitHub to find candidates for their design teams by searching candidates who have built impressive projects.[13]

To examine whether a positive shock to OI adoption, proxied by the introduction of GitHub, made it easier for firms to access talent, we rely on the GitHub Search API to obtain a listing of all organization accounts on the platform and match them to publicly traded firms in our sample. Although GitHub was launched in 2008, it had very limited activity in the first year of its launch. Hence, we focus on the two years surrounding 2009 and estimate the following difference-in-difference model:

$$\text{Net inventor flow}_{it} = \alpha_t + \beta_i + \gamma X_{it} + \delta \text{Treatment}_i \times \text{Post}_t + \eta \text{Post}_t + \theta \text{Treatment}_i + \varepsilon_{it} \quad (2)$$

where $Post_t$ takes the value of one for the period 2009–2011 and zero for the period 2007–2008. $Treatment_i$ is a time-invariant dummy variable that equals one for firms that did not engage in OI before 2009 but have appeared on GitHub afterward and equals zero for firms that had engaged in OI before 2009. Our variable of interest is the interaction term $Treatment_i \times Post_t$ that reflects the change in inventor flow between the two groups. Our regression includes the same vector of control variables, year fixed effects, and firm fixed effects, which subsume the standalone *Treatment* dummy variable. As shown in Table 7, the positive shock to OI led to a greater net inflow of inventors for firms affected by the introduction of GitHub,

[13] Kula.ai/blog/github-beginners-guide-source-candidates.

compared to other firms who had engaged in OI before GitHub. This evidence is consistent with the proposition that an improvement in the ability to conduct OI is associated with a greater inflow of talent.

5.1.3. Robustness

This section discusses several robustness checks of the relation between net inventor flow and OI.

5.1.3.1. Alternative model specifications

Cohn, Liu, and Wardlaw (2022) document that prior papers using skewed data are highly sensitive to the regression model employed. To address this concern, we follow their suggestion and re-estimate the baseline regression using several alternative models. Specifically, we use: i) fixed-effects Poisson pseudo-maximum likelihood model, in which the dependent variable is the raw number of net inventor flow; ii) OLS model with the raw number of net inventor flow as the dependent variable (without the inverse hyperbolic sine transformation); iii) the log transformation, that is, Ln(number of net inventor flow) as the dependent variable (without adding one to the log transformation); iv) scale the raw count by firm size, i.e., the exposure variable, to transform the outcome variable into a rate. The coefficients on the *% of OI positions* and *# of OI headlines* remain positive and significant at or below the 5% level, which indicates that our inferences are largely unchanged under alternative models (untabulated).

We note that 3-5% of firm-year observations in our sample contain more than 10 OI positions or headlines. Hence, our results may be driven by a handful of observations, which would limit the generalizability of our findings. To address this possibility, we re-run our analysis using a sample that removes these observations. Our results are robust to such an exclusion (untabulated).

Another caveat with our estimates is that they may not reflect the effects of OI engagements as omitted factors at firms with OI engagements may lead to both OI initiatives and a higher net inflow of inventors. Our strategy of including firm fixed effects in the OLS regressions partially mitigates the omitted variable concern if the unobservable firm characteristics biasing the results are constant over time. However, if the unobservable characteristics are time-varying, including firm fixed effects is not adequate to control for the endogeneity problem. For instance, firms with more open cultures might be more likely to engage in OI and be more successful in attracting productive inventors. To address this possibility, we directly control for culture in our regressions. Specifically, we rely on the cultural value score developed by Li, Mai, Shen, and Yan (2021), who show that their measure correlates positively with several business outcomes, including innovation, profitability, and risk-taking. Our results are robust to accounting for potential differences in culture for firms with OI (untabulated).

Additionally, we augment the baseline model by replacing year fixed effects with two pairs of fixed effects, i.e., the industry-year and state-year fixed effects. We include industry-year fixed effects to control for potential differential trends in net inventor flow and OI engagements across industries over time and to absorb technological shocks. We include state-year fixed effects to account for unobserved, time-varying state-level factors, such as the political economy or local business cycles, which may affect net inventor flow. We determine a firm's location state based on the location of its headquarters, which is usually where its major operations are located. Our main results continue to hold after including both industry-year and state-year fixed effects (untabulated).

5.1.3.2. Bartik IV

To further mitigate the possibility that our results are driven by omitted variables, we perform an instrumental variable regression using a shift-share/Bartik instrument (Bartik, 1991). One of the advantages of using Bartik instrument is that shift-share instruments rely on rather weak identifying assumptions. As some recent work has shown, shift-share instruments provide unbiased estimates of the treatment effect if either the share part (Goldsmith-Pinkham, Sorkin, and Swift, 2020) or the shift part is exogenous (Borusyak, Hull, and Jaravel, 2022); that is, it is not necessary that both parts be exogenous (Breuer, 2022).

We construct our shift-share instrument as follows. In the first step, we construct the pre-determined share part of our instrument. To strengthen the exogeneity assumption, we select 1999 as the base to increase the temporal distance between the base year and the starting year of our sample (2001). We use a firm's % of OI positions in 1999 as the share part of the instrument. In the second step, we construct the shift part of our instrument by focusing on the trend in OI positions within the 2-digit SIC industry. To improve the exogeneity of the industry trend, we exclude the focal firm and all same-industry firms that are located in the same state. Finally, we multiply a firm's OI positions in a base year (share part) by the growth in the OI positions of other firms within an industry (shift part) to obtain our shift-share instrument. It is likely that our shift-share instrument does not violate the exclusion restriction because it focuses only on the common trend that is pooled over all other companies within the same industry but located in other states. This common industry trend is unlikely to be directly related to net inventor flow at the focal firm because such industry changes are typically driven by macroeconomic factors that are exogenous to individual corporations.

In the first-stage regression, we regress *% of OI positions* on the Bartik instrument along with all other controls and fixed effects as specified in the baseline model. The coefficient on the Bartik instrument is positive and significant at the 1% level. More importantly, the F-statistic for weak instruments is 18.89 and it is significant at the 1% level, suggesting that the instrument is not weak. In the second-stage regressions, we continue to use net inventor flow as the dependent variable and include other independent variables and fixed effects as specified in the baseline model, except that we replace *% of OI positions* with *fitted % of OI positions*. Table 8 presents the corresponding estimates. The coefficients on fitted % of OI positions are positive and significant at the 5% level. Our results are similar if we use *% of OI headlines* instead.

Estimates using a shift-share instrument provide some confidence that our findings are not significantly plagued by omitted factors that jointly influence OI and net inventor flow. Nevertheless, we recognize that our approach to overcoming endogeneity has its limitations, which precludes us from identifying a causal relation and completely ruling out the possibility that our results might, at least partially, be driven by omitted variables. Given that the choice to engage in OI will always be endogenous, our findings should be interpreted with caution.

5.2. Innovation

In this section, we examine the relationship between OI and innovation quantity, efficiency, and strategy. We conjecture that the reshuffling of human capital documented earlier, along with broader access to external ideas, can lead to higher levels of innovation for firms with OI engagements. We rely on patents as a measure of the overall quantity of innovation because innovations are usually officially introduced to the public in the form of approved patents and patents are the most natural and measurable output from the process of innovation. We measure patent quantity as the number of patent applications filed by a firm in a given year that are eventually granted. Moreover, the application (rather than grant) year better captures the actual time of innovation. The dependent variable in Panel A of Table 9 is the number of patent applications at t+1 (Columns 1 and 4), t+2 (Columns 2 and 5), and t+3 (Columns 3 and 6). Similar to our earlier analysis, we apply the inverse hyperbolic sine transformation to the dependent variables to account for the right-skewness in the distribution of patent grants.

The results in Columns 1–3 indicate that firms with a higher percentage of OI positions have a greater volume of innovative output, as such firms receive more patents. Similarly, Columns 4–6 show that the number of OI headlines is positively related to the number of patents. This analysis suggests that OI initiatives help firms boost their innovation output. Yet, the innovation literature suggests that simple patent counts do not necessarily capture the economic importance of the associated inventions, as patents differ greatly in terms of their relative importance (e.g., Harhoff, Narin, Scherer, Vopel, 1999, Hall, Jaffe, Trajtenberg, 2005). Hence, firms with OI might be producing more patents, but of lower quality. To examine the relationship between OI and quality of innovation, we use two measures of the importance of corporate innovation: number of citations per patent and patent's economic value as measured by Kogan, Papanikolaou, Seru, and Stoffman (2017). Our analysis reveals that OI initiatives enhance not only the quantity of innovation output but also enable firms to generate higher-value patents (untabulated).

In Panels B and C of Table 9, we analyze the relation between OI and innovation efficiency, i.e., a firm's ability to generate patents and patent citations per dollar of research and development (R&D) investment. The denominator, R&D, measures resource input to innovation, whereas patents and citations are measures of innovative output. Following prior literature, we use two proxies for innovation efficiency: patents granted scaled by R&D capital (Panel B) and adjusted patent citations scaled by R&D expenses (Panel C). The results in both panels show a strong positive relation between OI and both measures of innovation efficiency, suggesting that OI indeed helps firms reduce their innovation costs and increase R&D efficiency.[14]

Next, we ask how OI impacts innovation strategy, i.e., whether it fosters exploration capabilities that could generate breakthroughs (i.e., radical innovations that open up whole new products and markets) or whether it strengthens exploitative innovation (i.e., incremental innovation that introduces relatively minor changes to the existing product). One of the widely cited benefits of OI is that it can give firms access to a wide range of fresh perspectives that might not exist within firm boundaries. Prior work has emphasized that the diversity of knowledge is particularly important for the development of radical innovations. Hence, firms engaging in OI might be more likely to engage in radical innovation. However, the resistance to adopting external knowledge might be stronger for more radical innovations and these innovations might be harder to integrate. Furthermore, OI participants might be less likely to share their most valuable insights, fearing that their ideas would not be properly acknowledged or compensated.

To examine whether OI engagements are associated with radical or incremental innovations, we develop several measures of innovation strategies. First, we follow prior studies (e.g., Balsmeier, Fleming, and Manso, 2017) and construct proxies for exploitative innovations, i.e., those that refine and extend existing knowledge, and exploratory innovations, i.e., those that require new knowledge or a departure from existing knowledge, using the extent to which a firm's patents rely on existing versus new knowledge. Specifically, we measure whether firms stay or deviate from known research areas, by using the degree of overlap between patents granted to the firm in year *t* and the existing patent portfolios held by the same

[14] Our results are robust if we scale the number of patents or citations by the 5-year cumulative R&D expenses assuming an annual depreciation rate of 20% as in Chan, Lakonishok, and Sougiannis (2001) and Lev, Sarath, and Sougiannis (2005).

firm up to firm t-1. Formally, we estimate internal search proximity as in Jaffe (1986) and Fitzgerald, Balsmeier, Fleming, and Manso (2021), as follows:

$$Internal\ Search\ Proximity_{i,t} = \frac{\sum_{k=1}^{K} f_{i,k,t}\, g_{i,k,t-1}}{(\sum_{k=1}^{K} f_{i,k,t}^2)^{\frac{1}{2}} (\sum_{k=1}^{K} g_{i,k,t-1}^2)^{\frac{1}{2}}}$$

where $f_{i,k,t}$ is the fraction of patents granted to firm i in year t that are in technology class k and $g_{i,k,t-1}$ is the fraction of all patents granted to firm i up to (and including) year t-1 that is in technology class k. *Internal Search Proximity* will be zero for a given firm year when there is no overlap in a firm's innovative output in year t with the firm's patent stock at time t-1 while *Internal Search Proximity* will equal one when the technology class the distribution of firm i's patents granted this year is identical to that of patents accumulated in previous years. Therefore, firms that are relatively more focused on exploration/(exploitation) when they have low/(high) values of *Internal Search Proximity*.

Second, we categorize patents according to how many citations they have received relative to other granted patents that have been applied for in the same technology class and year. This is intended to separate degrees of innovative outcomes, ranging from highly successful breakthroughs (highly cited) to completely failed inventions (not cited at all) and moderately successful outcomes that lie between. Specifically, following Balsmeier et al. (2017), we separate patents into those with citations in: the top 1% among all patents in the same three-digit patent class and application year (breakthrough patents); 2%-10% among all patents in the same three-digit patent class and application year (important patents); not in the top 10% but cited at least once (incremental patents); and never cited at all (little value patents).

Lastly, we separate innovations into product and process innovations. According to Chava, Oettl, and Subramanian (2013), product innovations result in the creation of new products and are thus more radical and riskier than process innovations, which mainly involve enhancing the efficiency of existing production processes. We follow Bena, Ortiz-Molina and Simintzi (2022) and break every patent down into process and non-process claims it contains. We compute a firm's Process Claims by summing the number of process claims contained in all of its patents filed in each year. Similarly, we compute a firm's Non-

Process Claims by summing the number of non-process claims contained in all of its patents filed each year.[15]

Table 10 reports the corresponding analysis, wherein the dependent variables are: internal search proximity of patent applications (Panel A), the number of breakthrough patents (Panels B and C, Column 1), the number of important patents (Panels B and C, Column 2), the number of incremental patents (Panels B and C, Column 3), the number of low-value patents (Panels B and C, Column 4), the number of process claims (Panel D), and the number of non-process claims (Panel E).

Panel A shows that both measures of OI are positively related to internal search proximity, suggesting that firms with OI engagements are more likely to generate patents that focus on exploitation rather than exploration. Given that the earlier stages of the product life cycle are typically characterized by explorative strategies, this result seems to suggest that firms are more likely to use OI in the later stages of the product life cycle. Furthermore, Panels B and C, which examine the relation between the nature of patents and *% of OI positions* and *# of OI headlines,* respectively, show that the estimated effect is by far the most significant and largest for incremental patents that receive at least one citation (but not in the top 10% of the distribution), while the estimated effect on particularly successful patents (top 1%) is very small in magnitude and insignificant when OI is measured by the *% of OI positions* and is weakly negative when OI is measured by the *# of OI headlines*. For brevity purposes, Panels B and C only tabulate patents filed in year *t*+1, however, our results are similar for patents filed in years *t*+2 and *t*+3. Lastly, the results in Panels D and E show a positive relation between OI and process innovation, but an insignificant relation between OI and product innovation. These results suggest that firms with OI engagements create more process patents rather than product patents, which further points towards an exploitative strategy.

Taken together, the results in this section suggest that the increased patent quantity for firms with OI is likely attributable to exploitative rather than exploratory innovation strategy. Firms seem to use external knowledge sources to "fine-tune" existing processes and innovate more efficiently.

[15] Our results are robust to using alternative measures, i.e., the citations-weighted number of process patents and the citations-weighted number of non-process patents.

5.3. Cost reduction and sales growth channels

In this section, we examine whether utilizing external sources of innovation contributes to firm value not only by attracting talent and boosting innovation but also by reducing costs and stimulating growth.

OI may help firms reduce costs, as firms may exploit other organizations' discoveries and find viable solutions at a fraction of the internal costs (Chesbrough and Crowther, 2006). We note that the reduction in costs might occur regardless of whether the outcomes of OI engagements are patented and whether new talent is hired. We examine the relation between OI engagements and broader measures of operating costs and efficiency, by focusing on total factor productivity in Panel A of Table 11 and the cost of goods sold in Panel B of Table 11. Panel A shows a robust positive relation between OI engagements and total factor productivity. The results in Panel B show that our measures of OI engagements are negatively related to COGS, however, the significance of this relation is weak.

Alternatively, firms may use OI as a marketing technique to promote their products or to better tailor their products to customer tastes, rather than to acquire talent or technology. We explore this empirically, in Table 12, where we analyze the relation between OI engagement and sales growth (Panel A) and new product introduction (Panel B). To identify the introduction of new products, we follow Mukherjee, Singh, and Zaldokas (2017) and search the CapitalIQ Key Development database for company press releases that are tagged under the subject "New Products" and where their headlines include keywords (with the roots of words) such as "Launch," "Product," "Introduce," "Begin," "Unveil." We then estimate the stock price reaction to product announcements using the standard market model. We define the number of new products as the number of product announcements with 3-day event CARs above the 75th percentile, after adjusting for firm size and book-to-market ratio. Panel A shows that the relationship between OI initiatives and sales growth is consistently insignificant. Similarly, in Panel B, we do not find evidence to suggest that firms with OI have higher sales or introduce a greater number of new products. The lack of growth in sales and new products is consistent with our earlier results showing no significant relation between OI and product innovation.

Taken together, the results in this section suggest that firms are likely to use OI to improve their efficiency and cut costs, rather than to grow sales.

6. Conclusion

Firms have increasingly attempted to improve their performance by tapping into sources of external knowledge (Chesbrough, 2003; Fey and Birkinshaw, 2005; Laursen and Salter, 2006). Indeed, for many of today's most successful companies, such as Amazon, Apple, Facebook, Google, Microsoft, and Tencent, openness, or at least some degree of openness, constitutes an essential part of their business model (see e.g., Nambisan, Siegel, and Kenney, 2018). Yet, the presence of valuable external knowledge does not imply that the inflow of new ideas into the organization is an automatic or easy process. Gains from open innovation might be difficult to appropriate and intellectual property difficult to protect.

Using a novel dataset that identifies OI initiatives from news articles and job descriptions, we find that OI engagements, on average, are value-increasing. This result can be explained by the reshuffling of inventors, wherein more productive inventors join these firms, and a higher level of innovation output. Our further analysis suggests that the increase in innovation comes mainly from patents in areas the firm has previously patented in, rather than breakthrough innovations. We show that the value creation also comes from the cost reduction, but not from sales growth.

The empirical evidence presented in this paper suggests that the corporate approach to innovation has a first-order effect on firm performance and that substantial differences exist in the innovation performance of firms with open and closed innovation paradigms. However, our results do not imply that firms should exclusively focus on external innovation. In fact, prior studies suggest that relying exclusively on external sourcing can result in a competitive disadvantage because a competence loss leads to an inability to capture the returns to innovation (Teece, 1986). Instead, our analysis suggests that firms focusing exclusively on internal sourcing might benefit from opening up their innovation processes and finding the right balance between internal and external sources of innovation.

Whereas our paper highlights the direct benefits to the firms engaging in OI, future research can explore spillover effects that may accrue to the broader ecosystem, such as subsequent industry-wide patent filings, overall increases in sectoral R&D intensity, improvements in innovation-related workforce skills, or the emergence of new technology clusters.

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Figure 1. Distribution of OI positions and OI headlines over time

This figure plots the number of our sample firms with at least one OI headline or OI position over the period 2001–2020.

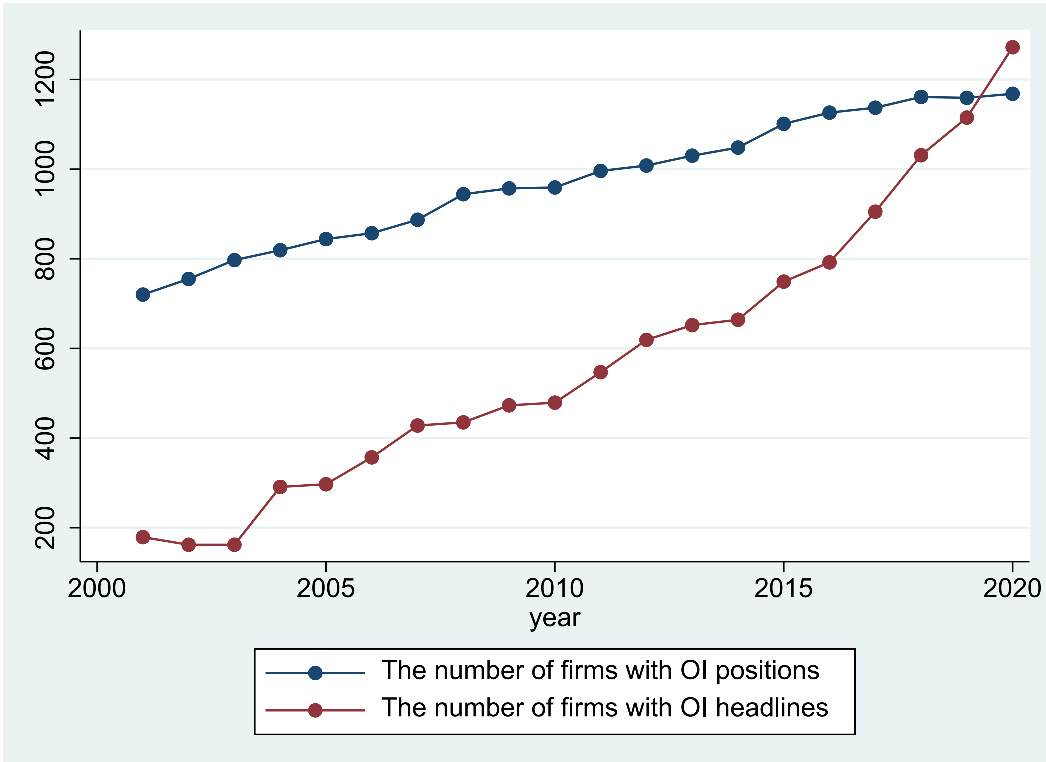

Table 1. Descriptive statistics

This table presents descriptive statistics, based on a sample of 3,917 firms over the period 2001–2020 (30,413 firm-year observations). Variable definitions are given in Appendix B.

	Mean	Standard deviation	25th percentile	Median	75th percentile
	(1)	(2)	(3)	(4)	(5)
Open innovation					
# OI positions	2.29	8.09	0.00	0.00	1.00
# OI headlines	1.22	5.95	0.00	0.00	0.00
Dependent variables					
# of patents	14.37	57.96	0.00	0.00	3.00
Citations	123.04	539.47	0.00	0.00	9.00
Patent value	1083.12	5468.20	6.88	39.28	263.40
Internal search proximity	0.71	0.31	0.55	0.83	0.95
Breakthrough patents	2.97	45.41	0.00	0.00	0.00
Important patents	2.31	26.41	0.00	0.00	0.00
Incremental patents	8.66	116.51	0.00	0.00	0.00
Low value patents	12.06	107.92	0.00	00.00	1.00
Process claims	98.26	1203.93	0.00	0.00	5.00
Non-process claims	457.56	3617.99	0.00	0.00	24.00
Patents/R&D	724.26	2421.09	0.00	14.50	240.69
Citations/R&D	5509.00	18122.34	0.00	53.36	1556.95
Leaver	4.91	37.79	0.00	0.00	1.00
New hire	12.28	89.64	0.00	0.00	1.00
Net new hire	7.38	57.09	0.00	0.00	0.00
Net patents	9.67	161.99	0.00	0.00	0.00
Net citations	66.33	31495.91	0.00	0.00	0.00
Firm characteristics					
Ln (Firm size)	6.97	1.92	5.62	6.88	8.25
Cash/Assets	0.20	0.23	0.04	0.11	0.28
Missing R&D indicator	0.39	0.49	0.00	0.00	1.00
R&D/Sales	0.06	0.11	0.00	0.00	0.06
ROA	0.09	0.19	0.0625	0.12	0.18
Asset tangibility	0.47	0.39	0.1569	0.35	0.72
Leverage	0.23	0.21	0.0264	0.20	0.35
Capex	0.05	0.06	0.0154	0.03	0.06
M/B	2.11	1.51	1.1698	1.60	2.45
HHI	0.08	0.07	.0324	0.04	0.09
Ln (Firm age)	2.76	0.85	2.1972	2.89	3.47

Table 1 (continued)

	Mean	Standard deviation	25th percentile	Median	75th percentile
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Firm characteristics (continued)					
Ln (CEO age)	4.02	0.14	3.9318	4.03	4.11
CEO/Chair duality	0.49	0.50	0.00	0.00	1.00
Outsider CEO	0.24	0.43	0.00	0.00	0.00

Table 2. Open innovation

Panel A reports the proportion of firms with OI headlines and OI positions, stratified by 12 Fama-French industry categories. Panel B reports the distribution of firm-year observations, stratified by the frequency of OI positions/headlines.

Panel A. OI by industry

	Percentage of OI positions	Percentage of OI headlines
Food, tobacco, textiles, apparel, leather, and toys	26.2%	14.2%
Cars, TV's, furniture, and household appliances	25.8%	15.7%
Machinery, trucks, planes, paper, and commercial printing	25.0%	8.1%
Oil, gas, coal extraction and products	21.2%	11.4%
Chemicals and applied products	35.5%	17.0%
Computers, software, and electronic equipment	50.9%	18.6%
Telephone and television transmission	36.9%	17.0%
Utilities	19.2%	7.7%
Wholesale, retail, and some services	28.6%	14.1%
Healthcare, medical equipment, and drugs	31.8%	8.9%
Financials	29.3%	12.4%
Mines, construction, building materials, transportation, and entertainment	28.3%	12.5%
Full sample	32.7%	13.1%

Panel B. Frequency of annual OI events

	Based on OI positions	Based on OI headlines
No OI	67.3%	86.9%
Between 1 and 5 OI	24.4%	8.5%
Between 6 and 10 OI	3.4%	1.6%
> 10 OI	4.9%	3.0%

Table 3. Determinants

This table presents estimates from ordinary least squares estimations using a panel of firm-year data. The dependent variable in Columns 1 and 3 is the natural logarithm of the number of positions with OI keywords, scaled by the total employment. The dependent variable in Columns 2 and 4 is the natural logarithm of the number of news headlines with OI keywords. Regressions in Columns 1 and 2 (3 and 4) control for year and 3-digit SIC industry (firm) fixed effects and include a constant (not shown). Variable definitions are in Appendix B. *t*-statistics are shown in parentheses. Standard errors are adjusted for heteroskedasticity (White, 1980) and are clustered by firm. *, **, *** denotes significance at 0.10, 0.05, 0.01 levels, respectively.

	Ln (% of OI positions)	**Ln (# of OI headlines)**	**Ln (% of OI positions)**	**Ln (# of OI headlines)**
	(1)	**(2)**	**(3)**	**(4)**
Ln(Firm size)	0.039***	0.155***	0.006	0.033***
	(9.83)	(13.14)	(0.46)	(2.57)
Cash/Assets	0.201***	0.179***	0.048	-0.005
	(4.11)	(2.97)	(1.00)	(-0.10)
Missing R&D indicator	-0.073***	-0.092***	-0.013	-0.004
	(-4.82)	(-3.27)	(-0.81)	(-0.11)
R&D/Sales	0.512***	0.145*	-0.048	-0.012
	(4.09)	(1.95)	(0.92)	(-0.36)
ROA	0.092***	0.008	-0.032	-0.009
	(2.78)	(0.28)	(-1.54)	(-0.58)
Asset tangibility	-0.024	-0.009	-0.006	-0.073
	(-1.22)	(-0.31)	(-0.19)	(-1.52)
Leverage	-0.061*	-0.045	-0.034	-0.057
	(-1.93)	(-1.03)	(-0.96)	(-1.35)
Capex	-0.060	0.003	0.016	-0.207*
	(-0.93)	(0.03)	(0.27)	(-1.91)
M/B	0.003	0.036***	-0.009**	-0.002
	(0.59)	(6.68)	(-2.05)	(-0.46)
HHI	-0.068	0.153	-0.006	0.126
	(-0.69)	(0.89)	(-0.06)	(0.76)
Ln(Firm age)	-0.016**	0.026**	0.045**	0.012
	(-2.03)	(2.26)	(2.24)	(0.50)
Alliances/Joint ventures	0.055***	0.083***	0.023***	0.049***
	(5.00)	(5.52)	(2.81)	(4.34)
Ln (CEO age)	-0.161***	-0.031	-0.014	0.020
	(-3.64)	(-0.51)	(-0.34)	(0.31)
CEO/Chair duality	-0.002	-0.009	-0.017*	-0.000
	(-0.16)	(-0.49)	(-1.74)	(-0.01)
Outsider CEO	-0.024	-0.015	-0.015	-0.004
	(-1.63)	(-0.70)	(-1.04)	(-0.19)
Industry and year fixed effects	Yes	Yes	No	No
Firm and year fixed effects	No	No	Yes	Yes
Number of observations	27,301	27,301	27,301	27,301
Adjusted R-squared	0.213	0.267	0.594	0.649

Table 4. Cumulative announcement returns

This table presents announcement returns for a sample of 20,222 OI engagements featured in the news. For mean and median asterisks indicate the differences from zero based on a *t*-test and signed rank test, respectively. The differences between sub-samples are based on *t*-test. *, **, *** denotes significance at 0.10, 0.05, 0.01 levels, respectively.

Panel A: Baseline results

	Mean	**Median**
CAR [-1:0]	0.081%***	0.040%***
CAR [-1:+1]	0.100%***	0.053%***
CAR [-3:0]	0.122%***	0.075%***

Panel B: High-tech

	Not high-tech	**High-tech**	**Difference**
CAR [-1:0]	0.052%***	0.110%***	0.057%*
CAR [-1:+1]	0.066%***	0.125%***	0.059%*
CAR [-3:0]	0.080%***	0.164%***	0.084%**

Panel C: Industry competition

	Low competition	**High competition**	**Difference**
CAR [-1:0]	0.075%***	0.090%***	0.015%
CAR [-1:+1]	0.090%***	0.114%***	0.024%
CAR [-3:0]	0.104%***	0.146%***	0.042%

Panel D: Non-compete agreements

	Low enforcement	**High enforcement**	**Difference**
CAR [-1:0]	0.117%***	0.053%**	-0.064%**
CAR [-1:+1]	0.141%***	0.068%***	-0.073%**
CAR [-3:0]	0.182%***	0.075%***	-0.107%***

Table 5. Inventor relocation

This table presents estimates from ordinary least squares estimations. In Panel A, the dependent variable is the number of a firm's newly hired inventors in a given year. In Panel B, the dependent variable is the number of a firm's inventors who leave for other firms in a given year. In Panel C, the dependent variable is the difference between the number of newly hired inventors and the number of leaving inventors. The dependent variables have been transformed using the inverse hyperbolic sine transformation. All regressions control for year and firm fixed effects and include a constant (not shown). Variable definitions are in Appendix B. *T*-statistics are shown in parentheses. Standard errors are adjusted for heteroskedasticity (White, 1980) and are clustered by firm. *, **, *** denotes significance at 0.10, 0.05, 0.01 levels, respectively.

Panel A: New hires

	New hires					
	t+1	*t*+2	*t*+3	*t*+1	*t*+2	*t*+3
	(1)	(2)	(3)	(4)	(5)	(6)
Ln (% of OI positions)	0.045***	0.041***	0.032			
	(3.18)	(2.46)	(1.63)			
Ln (# of OI headlines)				0.063***	0.057***	0.049***
				(5.79)	(4.53)	(3.46)
Firm and CEO characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firm and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	30,413	28,756	26,052	30,413	28,756	26,052
Adjusted R-squared	0.849	0.813	0.800	0.850	0.813	0.800

Panel B: Leavers

	Leavers					
	t+1	*t*+2	*t*+3	*t*+1	*t*+2	*t*+3
	(1)	(2)	(3)	(4)	(5)	(6)
Ln (% of OI positions)	0.064***	0.076***	0.059***			
	(4.41)	(4.86)	(3.47)			
Ln (# of OI headlines)				0.042***	0.040***	0.035***
				(4.15)	(3.84)	(2.97)
Firm and CEO characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firm and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	30,413	28,756	26,052	30,413	28,756	26,052
Adjusted R-squared	0.816	0.781	0.768	0.816	0.780	0.768

Panel C: Net new hires

	Net new hires					
	***t*+1**	***t*+2**	***t*+3**	***t*+1**	***t*+2**	***t*+3**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Ln (% of OI positions)	0.210***	0.057	-0.004			
	(4.44)	(1.36)	(-0.09)			
Ln (# of OI headlines)				0.118***	0.135***	0.104***
				(4.02)	(4.23)	(3.48)
Firm and CEO characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firm and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	29,964	28,280	25,622	29,964	28,280	25,622
Adjusted R-squared	0.443	0.444	0.457	0.442	0.445	0.458

Table 6. Inventor productivity

This table presents estimates from ordinary least squares estimations. In Panel A, the dependent variable is the difference between the number of patents generated by the newly hired and leaving inventors. In Panel B, the dependent variable is the difference between the number of citations generated by the newly hired and leaving inventors. The dependent variables have been transformed using the inverse hyperbolic sine transformation. All regressions control for year and firm fixed effects and include a constant (not shown). Variable definitions are in Appendix B. *T*-statistics are shown in parentheses. Standard errors are adjusted for heteroskedasticity (White, 1980) and are clustered by firm. *, **, *** denotes significance at 0.10, 0.05, 0.01 levels, respectively.

Panel A: Net patents

	Net patents					
	***t*+1**	***t*+2**	***t*+3**	***t*+1**	***t*+2**	***t*+3**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Ln (% of OI positions)	0.227***	0.062	0.006			
	(3.41)	(0.98)	(0.09)			
Ln (# of OI headlines)				0.104**	0.087*	-0.001
				(2.53)	(1.93)	(-0.02)
Firm and CEO characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firm and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	29,964	28,280	25,622	29,964	28,280	25,622
Adjusted R-squared	0.062	0.058	0.072	0.062	0.058	0.072

Panel B: Net citations

	Net citations					
	***t*+1**	***t*+2**	***t*+3**	***t*+1**	***t*+2**	***t*+3**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Ln (% of OI positions)	0.475***	0.150	0.122			
	(4.55)	(1.42)	(1.21)			
Ln (# of OI headlines)				0.151**	0.122*	0.084
				(2.23)	(1.90)	(1.27)
Firm and CEO characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firm and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	29,964	28,280	25,622	29,964	28,280	25,622
Adjusted R-squared	0.037	0.037	0.041	0.035	0.037	0.041

Table 7. GitHub introduction

This table presents estimates from ordinary least squares estimations. The dependent variable is the difference between the number of newly hired inventors and the number of leaving inventors. The dependent variable has been transformed using the inverse hyperbolic sine transformation. $Post_t$ takes the value of one for the period 2009–2011 and zero for the period 2007–2008. $Treatment_i$ is a time-invariant dummy variable that equals one for firms that did not engage in OI prior to 2009, but have appeared on GitHub afterwards and equals zero for firms that had engaged in OI prior to 2009. All regressions control for year and firm fixed effects and include a constant (not shown). Variable definitions are in Appendix B. *T*-statistics are shown in parentheses. Standard errors are adjusted for heteroskedasticity (White, 1980) and are clustered by firm. *, **, *** denotes significance at 0.10, 0.05, 0.01 levels, respectively.

	Net new hires		
	***t*+1**	***t*+2**	***t*+3**
	(1)	**(2)**	**(3)**
Treatment × Post	0.140***	0.087*	0.029
	(2.65)	(1.68)	(0.47)
Firm and CEO characteristics	Yes	Yes	Yes
Firm and year fixed effects	Yes	Yes	Yes
Number of observations	10,330	9,672	9,085
Adjusted R-squared	0.692	0.690	0.682

Table 8. Instrumental variable estimation with a Bartik instrument

This table presents estimates from ordinary least squares estimations and reports the results of the second stage of a 2SLS estimation. The dependent variable is the difference between the number of newly hired inventors and the number of leaving inventors. The dependent variable has been transformed using the inverse hyperbolic sine transformation. Fitted % of OI positions (# of OI headlines) is the predicted value of % of OI positions (# of OI headlines), which is estimated by regressing % of OI positions (# of OI headlines) on shift-sharing instrument, firm and CEO characteristics, firm and year fixed effects. All regressions control for year and firm fixed effects and include a constant (not shown). Variable definitions are in Appendix B. *T*-statistics are shown in parentheses. Standard errors are adjusted for heteroskedasticity (White, 1980) and are clustered by firm. *, **, *** denotes significance at 0.10, 0.05, 0.01 levels, respectively.

	Net new hires					
	***t*+1**	***t*+2**	***t*+3**	***t*+1**	***t*+2**	***t*+3**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Fitted Ln (% of OI positions)	2.783**	3.114**	2.474			
	(2.30)	(2.00)	(1.57)			
Fitted Ln (# of OI headlines)				0.187*	0.202*	0.107
				(1.78)	(1.87)	(1.01)
Firm and CEO characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firm and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	17,547	15,738	14,137	17,547	15,738	14,137

Table 9. Innovation quantity and efficiency

This table presents estimates from ordinary least squares estimations. The dependent variable in Panel A is the number of patent applications. The dependent variable in Panel B is the number of patent applications scaled by R&D expenses. The dependent variable in Panel C is the adjusted number of citations scaled by the R&D expense. The dependent variables in Panels A–C have been transformed using the inverse hyperbolic sine transformation. All regressions control for year and firm fixed effects and include a constant (not shown). Variable definitions are in Appendix B. *T*-statistics are shown in parentheses. Standard errors are adjusted for heteroskedasticity (White, 1980) and are clustered by firm. *, **, *** denotes significance at 0.10, 0.05, 0.01 levels, respectively.

Panel A: Patents

	Patents					
	t+1	*t*+2	*t*+3	*t*+1	*t*+2	*t*+3
	(1)	(2)	(3)	(4)	(5)	(6)
Ln (% of OI positions)	0.099***	0.125***	0.107***			
	(4.85)	(5.39)	(4.25)			
Ln (# of OI headlines)				0.076***	0.096***	0.096***
				(5.04)	(5.59)	(5.06)
Firm and CEO characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firm and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	30,413	28,756	26,052	30,413	28,756	26,052
Adjusted R-squared	0.880	0.845	0.833	0.878	0.844	0.833

Panel B: Patents/R&D

	Patents/R&D					
	t+1	*t*+2	*t*+3	*t*+1	*t*+2	*t*+3
	(1)	(2)	(3)	(4)	(5)	(6)
Ln (% of OI positions)	0.104***	0.138***	0.144***			
	(2.81)	(3.54)	(3.44)			
Ln (# of OI headlines)				0.120***	0.169***	0.173***
				(3.14)	(4.19)	(4.19)
Firm and CEO characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firm and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	14,725	14,471	13,027	14,725	14,471	13,027
Adjusted R-squared	0.792	0.774	0.771	0.792	0.775	0.771

Panel C: Citations/R&D

	Citations/R&D					
	***t*+1**	***t*+2**	***t*+3**	***t*+1**	***t*+2**	***t*+3**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Ln (% of OI positions)	0.170*** (3.03)	0.160*** (3.40)	0.166*** (3.28)			
Ln (# of OI headlines)				0.160*** (3.20)	0.128*** (3.04)	0.094** (2.23)
Firm and CEO characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firm and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	13,441	15,396	14,483	13,441	15,396	14,483
Adjusted R-squared	0.771	0.770	0.778	0.771	0.770	0.777

Table 10. Innovation strategy

This table presents estimates from ordinary least squares estimations. The dependent variable in Panel A is the degree of overlap between patents granted to the firm in year *t* and the existing patent portfolios held by the same firm up to firm *t*-1, as in Jaffe (1986) and Fitzgerald, Balsmeier, Fleming, and Manso (2021). The dependent variables in Panels B and C are: the number of patents that fall in the top 1% of the citation distribution within patent class and application year (Column 1); the number of patents that fall in the top 10% of the citation distribution within patent class and application year (excluding the top 1%) (Column 2); the number of patents that are cited but do not fall in the top 10% of the citation distribution (Column 3); the number of patents that are not cited (Column 4). The dependent variable in Panel D (E) is a firm's Process Claims, i.e., the sum of the number of process claims contained in all of its patents filed in a given year (a firm's Non-Process Claims, i.e., the sum of the number of non-process claims contained in all of its patents filed in a given year). The dependent variables in Panels B-E have been transformed using the inverse hyperbolic sine transformation. All regressions control for year and firm fixed effects and include a constant (not shown). Variable definitions are in Appendix B. *T*-statistics are shown in parentheses. Standard errors are adjusted for heteroskedasticity (White, 1980) and are clustered by firm. *, **, *** denotes significance at 0.10, 0.05, 0.01 levels, respectively.

Panel A: Internal Search Proximity

	Internal search proximity					
	t+1	*t*+2	*t*+3	*t*+1	*t*+2	*t*+3
	(1)	(2)	(3)	(4)	(5)	(6)
Ln (% of OI positions)	0.010*	0.013**	0.011*			
	(1.90)	(2.28)	(1.88)			
Ln (# of OI headlines)				0.003	0.008*	0.013***
				(0.72)	(1.68)	(2.61)
Firm and CEO characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firm and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	10,150	9,165	8,242	10,150	9,165	8,242
Adjusted R-squared	0.518	0.520	0.526	0.518	0.520	0.527

Panel B: The distribution of citations – OI positions

	Breakthrough (Top 1% citations)	Important (Top 2%-10% citations)	Incremental (Not in top 10%, but cited)	Low value (never cited)
	(1)	(2)	(3)	(4)
Ln (% of OI positions)	-0.013	0.047***	0.121***	0.095***
	(-0.79)	(2.81)	(4.22)	(4.33)
Firm and CEO characteristics	Yes	Yes	Yes	Yes
Firm and year fixed effects	Yes	Yes	Yes	Yes
Number of observations	30,413	30,413	30,413	30,413
Adjusted R-squared	0.594	0.664	0.697	0.817

Panel C: The distribution of citations – OI headlines

	Breakthrough (Top 1% citations)	Important (Top 2%-10% citations)	Incremental (Not in top 10%, but cited)	Low value (never cited)
	(1)	(2)	(3)	(4)
Ln (# of OI headlines)	-0.023*	0.055**	0.184***	0.019
	(-1.74)	(4.47)	(7.69)	(1.16)
Firm and CEO characteristics	Yes	Yes	Yes	Yes
Firm and year fixed effects	Yes	Yes	Yes	Yes
Number of observations	30,413	30,413	30,413	30,413
Adjusted R-squared	0.594	0.664	0.700	0.817

Panel D: Process innovation

	Process claims					
	t+1	*t*+2	*t*+3	*t*+1	*t*+2	*t*+3
	(1)	(2)	(3)	(4)	(5)	(6)
Ln (% of OI positions)	0.391***	0.124**	0.008			
	(7.62)	(2.54)	(0.16)			
Ln (# of OI headlines)				0.235***	0.237***	0.133***
				(6.01)	(5.73)	(3.08)
Firm and CEO characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firm and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	30,160	27,015	24,082	30,160	27,015	24,082
Adjusted R-squared	0.502	0.514	0.524	0.501	0.516	0.525

Panel E: Non-process innovation

	Non-process claims					
	t+1	*t*+2	*t*+3	*t*+1	*t*+2	*t*+3
	(1)	(2)	(3)	(4)	(5)	(6)
Ln (% of OI positions)	0.048	0.041	0.001			
	(1.09)	(0.87)	(0.01)			
Ln (# of OI headlines)				0.055*	0.052	0.017
				(1.82)	(1.64)	(0.50)
Firm and CEO characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firm and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	30,159	27,014	24,081	30,159	27,014	24,081
Adjusted R-squared	0.772	0.770	0.767	0.773	0.770	0.767

Table 11. Cost reduction channel

This table presents estimates from ordinary least squares estimations. The dependent variable in Panel A is total factor productivity. The dependent variable in Panel B is cost of goods sold. All regressions control for year and firm fixed effects and include a constant (not shown). Variable definitions are in Appendix B. *T*-statistics are shown in parentheses. Standard errors are adjusted for heteroskedasticity (White, 1980) and are clustered by firm. *, **, *** denotes significance at 0.10, 0.05, 0.01 levels, respectively.

Panel A: Total factor productivity

	TFP					
	t+1	*t*+2	*t*+3	*t*+1	*t*+2	*t*+3
	(1)	(2)	(3)	(4)	(5)	(6)
Ln (% of OI positions)	0.043**	0.046***	0.029**			
	(2.49)	(3.08)	(2.09)			
Ln (# of OI headlines)				0.010	0.025***	0.023***
				(1.62)	(3.16)	(3.47)
Firm and CEO characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firm and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	29,164	25,034	19,989	29,164	25,034	19,989
Adjusted R-squared	0.722	0.735	0.771	0.722	0.735	0.777

Panel B: COGS

	COGS					
	t+1	*t*+2	*t*+3	*t*+1	*t*+2	*t*+3
	(1)	(2)	(3)	(4)	(5)	(6)
Ln (% of OI positions)	-0.148***	-0.024	-0.015			
	(-4.09)	(-1.20)	(-0.64)			
Ln (# of OI headlines)				-0.053***	-0.017*	-0.008
				(-2.71)	(-1.78)	(-0.89)
Firm and CEO characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firm and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	30,410	26,047	20,733	30,410	26,047	20,733
Adjusted R-squared	0.934	0.958	0.962	0.933	0.958	0.962

Table 12. Growth channel

This table presents estimates from ordinary least squares estimations. In Panel A, the dependent variable is the annual sales growth. In Panel B, the dependent variable is the number of new products. The dependent variables in Panel B have been transformed using the inverse hyperbolic sine transformation. All regressions control for year and firm fixed effects and include a constant (not shown). Variable definitions are in Appendix B. *T*-statistics are shown in parentheses. Standard errors are adjusted for heteroskedasticity (White, 1980) and are clustered by firm. *, **, *** denotes significance at 0.10, 0.05, 0.01 levels, respectively.

Panel A: Sales growth

	Sales growth					
	***t*+1**	***t*+2**	***t*+3**	***t*+1**	***t*+2**	***t*+3**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Ln (% of OI positions)	-0.009	-0.004	-0.002			
	(-1.52)	(-0.65)	(-0.25)			
Ln (# of OI headlines)				-0.003	0.002*	-0.002
				(-0.98)	(1.78)	(-0.25)
Firm and CEO characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firm and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	29,996	28,416	25,777	29,996	28,416	25,777
Adjusted R-squared	0.235	0.222	0.199	0.235	0.222	0.199

Panel B: New products

	New products					
	***t*+1**	***t*+2**	***t*+3**	***t*+1**	***t*+2**	***t*+3**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Ln (% of OI positions)	-0.016	-0.014	-0.012			
	(-1.21)	(-0.86)	(-0.74)			
Ln (# of OI headlines)				-0.004	-0.011	-0.014
				(-0.33)	(-0.96)	(-1.07)
Firm and CEO characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firm and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	30,413	28,756	26,052	30,413	28,756	26,052
Adjusted R-squared	0.731	0.726	0.721	0.731	0.774	0.773

Appendix A: Examples of OI headlines and job descriptions

Company	Job Title	Job Duties
Coca-Cola	Founder Open Innovation Program	Sourced talent, technical knowledge building, and solutions through open innovation, to meet specifications, business requirements, and innovation goals of a global corporation. Launched the External Technology Acquisition open innovation program, creating and recruiting a network of 6 team members, 70 motivated internal subject matter experts, and establishing 9 global technology hubs.
Bayer Material Science	Research Fellow & Head, Business Growth Services	Led group of 5 professionals to provide open innovation services to the 3 BMS Business Units (Polyurethanes, Polycarbonates, and Coatings, Adhesives & Specialties) Leveraged external network of university and open innovation service providers for technology scouting, assessment, analysis, and development of business opportunities. Managed open innovation and government contracts & compliance; tracked metrics and key performance indicators for open innovation across BMS
Humana	Strategic Consultancy – insights consultant	Developed and led 16 open innovation and social business campaigns across all lines of business with Humana leadership that resulted in $2M+ savings and operational transformations that drove improved associate engagement.
Shell	Game Changer	Manage a portfolio of open innovation projects related to energy that have potential for step change impact in Shell's business
PepsiCo	R&D Strategy Director-Global Dairy and Chocolate Center of Excellence	Responsible for white sheet development of new R&D capabilities, including evaluation of open innovation partnerships, location selection, internal wiring with new R&D model and development of technical strategy inputs for Strategic Growth and Capability Plans.
Procter & Gamble	Intellectual Property and Front End Innovation Manager	Develop intellectual property and competitive response strategies for open innovation and internal development initiatives in Healthcare, manage P&G's global Healthcare intellectual property portfolio, grow organizational capability for intellectual property, lead upstream R&D for Healthcare.
Kimberly-Clark	Senior Marketing Director - Corporate Innovation	Pioneered the development of open innovation systems including Huggies MomInspired ... a 60+ start-up ecosystem of mom-founded businesses pioneering the future of baby and childcare products.
Comcast	Vice President, Startup Engagement, Business Development	With insights from 1500+ founders and business leaders, build vision, go-to-market strategy and roadmap for first Startup Engagement open innovation function for Fortune 40. Launch and operate accelerator, new tech pilot program, and national speakers/educational series.
Novartis	Global Head of Supplier Performance and Innovation	Responsible for supplier relationship management and open innovation programs across the organization for all OPEX and CAPEX suppliers (including commercial, R&D, IT, direct material, corporate services) driving innovative solutions, operational excellence and quality performance in support of the enterprise business strategies.
Microsoft	Senior Paralegal - Open Innovation	Leads and demonstrates accountability for projects within the Open Innovation Counselling team and/or on parts of larger projects outside the practice group.

Appendix A. (continued)

Company	Headline	Date
AES Corp.	aes announces winners of open innovation contest at 2017 innovation congress	07/12/17
AT&T Inc.	at&t launches dedicated certification lab for emerging devices, reinforces 'open innovation' leadership	09/02/09
Procter & Gamble Corp.	procter & gamble launches open innovation website to find innovators for most pressing needs	02/22/13
IBM	ibm to open innovation center in thailand	08/15/16
AT&T Inc.	opportunity knocks for mobile developers - enter the at&t mobile app hackathon	02/27/12
Colgate-Palmolive Co.	colgate-palmolive and black girls code to host second hackathon in san francisco	09/22/17
Comcast Corp.	comcast nbc universal announces launch of startup accelerator ...	03/23/17
Microsoft Corp.	microsoft dynamics unveils new crm accelerators	07/09/09
Target Corp.	target : after intense summer retail accelerator, five startups will pilot services at target	10/11/18
Uber Technologies Inc.	uber to open center for research on self-driving cars	02/02/15
Adidas AG	inside the adidas innovation laboratory	06/21/12
Caterpillar Inc.	caterpillar celebrates grand opening of data innovation lab	02/20/15
IBM	ibm announces creation of services innovation lab	07/28/11
Under Armour Inc.	under armour's new innovation lab features robots that make sneakers - take a look inside	06/28/16
Deutsche Bank AG	deutsche bank continues fintech drive with ny innovation lab	03/21/17
Xerox Holdings Corp.	xerox : innovation lab partners with xerox, parc to develop solutions that improve health care	08/21/17

Appendix B: Variable definitions

Variable	Definitions
	Panel A: Dependent variables
% of OI positions	The number of positions with OI keywords in a given year, scaled by the number of employees.
# of OI headlines	The number of news headlines with OI keywords in a given year.
Patents	The number of patent applications filed in a given year.
New hire	The number of a firm's newly hired inventors in a given year.
Leaver	The number of a firm's inventors who leave for other firms in a given year.
Net hire	The difference between the number of newly hired inventors and the number of leaving inventors.
Net patents	The difference between the number of patents generated by the newly hired inventors and the number patents generated by the leaving inventors.
Net citations	The difference between the number of citations generated by the newly hired inventors and the number of citations generated by the leaving inventors.
Citations (lifetime/3/5)	Total number of lifetime (first 3/5 year) citations received by the patents applied for by a firm in a given year.
Patent's economic value	Patent value metric as measured by Kogan et al. (2017).
Internal search proximity	The degree of overlap between patents granted to the firm in year t and the existing patent portfolios held by the same firm up to firm t-1, constructed following Jaffe (1986) and Fitzgerald et al (2021).
Process claims	The sum of the number of process claims contained in all of its patents filed in a given year.
Non-process claims	The sum of the number of non-process claims contained in all of its patents filed in a given year.
Breakthrough patents	The number of patents that fall in the top 1% percentile of the citation distribution within patent class and application year.
Important patents	The number of patents that fall in the top 10% centile of the citation distribution within patent class and application year (excluding the top 1%).
Incremental patents	The number of patents that are cited but do not fall in the top 10% of the citation distribution.
Low value patents	The number of patents that are not cited.
Patents/R&D	The ratio of firm patents scaled by the R&D expense.
Citations/R&D	Adjusted number of citations scaled by the R&D expense.
COGS	Cost of goods sold.
TFP	Total factor productivity is computed as residuals from industry-specific regressions of revenue on the number of employees, fixed assets, and year fixed effects.

Appendix B: Variable definitions *(continued)*

Panel B: Firm characteristics	
Firm size	Book value of total assets.
Cash/Assets	Cash, scaled by total assets.
Missing R&D indicator	Indicator variable that equals one if the firm has missing research and development expense, zero otherwise.
R&D/Sales	Research and development expense, scaled by sales.
ROA	Operating income before depreciation, scaled by book value of total assets.
Asset tangibility	Net property, plant, and equipment divided by total assets.
Leverage	Book value of debt divided by market value of total assets.
Capex	Capital expenditures, scaled by total assets
M/B	Market value of assets divided by book value of assets. Market value of assets is book value of total assets minus book value of equity plus market value of equity.
HHI	Herfindahl-Hirschman Index, based on sales.
Firm age	Firm age.
Alliances/Joint ventures	Indicator variable that equals one if there is at least one alliance/joint venture, zero otherwise.
CEO age	CEO's age as reported in BoardEx.
CEO/Chair duality	Indicator variable that equals one if the CEO is also the Chair of the board, zero otherwise.
Outsider CEO	Indicator variable that equals one if the CEO is appointed from outside the company ranks, zero otherwise.