Creativity without walls: The case of open innovation

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Abstract

We investigate the increasingly common open innovation (OI) initiatives, which supplement internal innovation with external sources via hackathons, crowdsourcing, and open innovation labs. These initiatives can be value-increasing as they may give access to a larger pool of talent, accelerate idea development, and spread out innovation-related risks. Yet, they may trigger the revelation of proprietary information and be hard to integrate. Using a novel dataset, we show that OI initiatives are positively related to an inflow of productive inventors and innovation. Further analysis shows that investors view OI initiatives positively and that the value-added stems from cost reductions, rather than sales growth.

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 relied on internally developed "proprietary" technologies, with research and development (R&D) being completely integrated within the boundaries of the firm (i.e., closed innovation). This paradigm started to shift in the late 1980s when an increasing number of firms began to access external knowledge for innovation by entering into well-defined formalized collaborations (e.g., alliances, partnerships, and joint ventures). The advent of technology and web-based platforms in the early 2000s, however, has drastically changed the scope and structure through which companies leverage external sources for innovation and gave rise to new forms of open innovation (hereafter, OI), which enabled companies to elicit a broader range of ideas through more flexible and less formal channels. Firms could now widely broadcast internal problems and invite a diverse set of external parties to offer solutions via tournaments, hackathons, crowdsourcing, or open innovation labs.[1]

The growing openness of firms was conceptualized by Chesbrough in 2003 as "open innovation," which is a broad philosophy that suggests that firms should explore a wide range of internal and external sources to boost their innovation efforts. In this paper, we focus on these new, more flexible multi-party forms of open innovation to provide the first large-sample evidence on factors that predict these OI initiatives and explore the implications of adopting such OI initiatives on corporate performance.

We start our analysis by examining the prevalence of these new OI initiatives and the factors that predict such engagements. Using a novel dataset that relies on data derived from individual-level LinkedIn profiles and news articles that feature OI initiatives, we construct two measures of OI engagements: i) the annual percentage of OI jobs at each firm, which captures firms' human capital investment in OI,[2] and ii)

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[1] For instance, in 2003 Philips opened up the High Tech Campus at Eindhoven to other companies. In 2006, MiPlaza was formalized as a separate division of Philips Research. This open innovation lab allows other companies to 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.

[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.

the annual # of OI headlines. Both measures show that the incidence of OI initiatives 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 initiatives 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. We do not find that firm performance predicts the propensity to engage in OI initiatives. In terms of within-firm variation, firms are more likely to engage in OI as they mature/grow bigger and start tapping into other external knowledge sources, e.g., joint ventures and alliances. R&D expense, however, becomes insignificant once we include firm fixed effects.

One of the advantages of new forms of OI is that they can give firms access to a broad pool of talent and may help firms recruit more talented employees. OI engagements can help reduce 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. Public forms of OI can also reduce information asymmetry about the employer and provide potential employees with information about an organization's less observable characteristics, e.g., culture, values, or tech skills. To test whether OI initiatives enable firms to have better access to human capital, we study the effects of OI initiatives 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 within-firm estimations suggest that OI engagements trigger changes in the composition of the inventor base. We find that OI engagements are associated with a significant inflow of inventors. Although we also document a significantly positive relation between OI engagements and inventor outflow, the net inflow of inventors is positive. We take several additional steps to verify that the relationship between OI and net inventor flow is robust to alternative model specifications, outliers, alternative fixed effects, and an instrumental variable estimation that relies on a shift-share/Bartik instrument. We also provide further evidence on the relation between OI initiatives and labor access by analyzing 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, as it enables firms to receive crowdsourced feedback on the projects they post on their public repositories. At the same time, GitHub allows companies to observe candidates' skills "in action" by providing access to candidates' actual code and real-world projects they contributed to. We focus on a five-year window around GitHub introduction and compare the change in net inventor inflow for firms that joined GitHub to those that did not join GitHub or engage in any other OI activities. We find that firms with public activity on GitHub have 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 correlated with a greater inflow of talent.

Yet, a greater inventor inflow does not necessarily imply that OI is beneficial. For instance, newly hired inventors might be less qualified than the departing ones. Even if new hires were more talented, OI initiatives may reduce incumbent inventors' incentives to innovate and stifle in-house creativity. Furthermore, the increased inventor turnover can be disruptive for inventor teams and have negative effects on innovation. To test these conjectures, we compare the productivity of departing inventors and new hires and explore the relationship between OI initiatives and firms' subsequent innovation quantity and quality. We find that the newly hired inventors are more productive compared to leavers in terms of both patents filed and citations per patent. Furthermore, we find a positive relation between OI engagements and future patent quantity and quality, as measured by citations and patents' economic value, which is consistent with the idea that OI may stimulate corporate innovation by attracting more productive inventors and/or boosting the productivity of the existing ones.

Our results thus far highlight some of the benefits associated with the new forms of OI. Yet, OI engagements also have their drawbacks. For instance, organizing innovative activity across the firm boundary increases the difficulty of coordination, communications, and knowledge integration. Furthermore, 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. The increased coordination costs and intellectual property risks associated with OI initiatives might prevent firms from realizing synergies from external collaborations and render OI initiatives value-decreasing. 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." 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.

To examine whether the benefits of new OI initiatives outweigh the costs, we estimate 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 mean CAR is 0.10% ($p<0.01$). The magnitude of stock price reactions in our sample is comparable to stock price responses to patent granted prior to the onset of new OI initiatives and were likely an outcome of closed innovation (mean three-day CAR of 0.12%), but lower than announcement returns for alliances (mean one-day CAR of 0.64%) and joint ventures (mean two-day CAR of 0.74%). We document that the market response to OI is more pronounced in firms for which first-mover advantage and faster innovation afforded by OI are critical, such as those operating in high-tech industries and in states where it is easier to attract talent due to weaker enforcement of non-compete agreements.

We conclude our analysis by examining whether the value-added likely stems from a reduction in operating costs or sales growth. OI initiatives might improve operating efficiency by enabling 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). Firms could also use new forms of OI as a marketing ploy to grow sales. For instance, OI initiatives might help increase publicity of firms' products, facilitate the creation of new products, or better tailor products to customer tastes. To examine the cost reduction 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 and a reduction in cost of goods sold, which is consistent with the idea that OI engagements may help firms convert their investments into output more efficiently. To explore the sales channel, we analyze the relationship between OI, sales growth and the introduction of new products. Empirically, we do not find support for this idea, as OI engagements are not associated with sales growth or the introduction of new products. These results suggest that firms use OI initiatives mostly help acquire talent and develop new technology that can reduce costs rather than to boost sales.

Our paper contributes 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 and sheds light on new forms of open innovation. In this respect, our paper is related to a new and growing literature in finance showing 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. We study a new setting wherein 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 large-scale dataset and novel measures of firm-level engagement in OI allow us to examine a broad range of OI engagements covering multiple industries over a longer period and provide a comprehensive picture of this growing phenomenon.[3]

Our paper is also related to contemporaneous work by Emery, Lim, and Ye (2024) and Coleman, Fronk, and Valentine (2025), who use GitHub to show that firms can benefit from making their software freely available to everyone (an *outbound* OI event). In contrast to these studies that focus on *outbound* OI, i.e., firms exporting their knowledge to broad audiences via GitHub, we focus on a broad range of *inbound* OI initiatives, wherein knowledge and resources flow into firms, which is more prevalent form of OI than outbound OI (Chesbrough and Crowther, 2006; Michelino, Caputo, Cammarano, and Lamberti, 2014). Taken together, our analysis highlights a novel and increasingly important approach to sourcing new ideas, which is particularly valuable in attracting top talent.

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. 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%.

[3] Earlier studies of OI in business strategy and management have mostly focused on the relation between OI and innovation and concerned theoretical debates based on case studies, single industries, surveys, in-depth interviews, and small samples, limiting the generalizability of their findings and resulting in a lack of agreement on the effects of OI. For instance, some authors found a positive, sometimes curvilinear, relationship between OI and innovation performance, while others found no relation, or even negative relationship (e.g. Laursen and Salter, 2006; Grimpe and Kaiser, 2010; Lifshitz-Assaf, Lebovitz, and Zalmanson, 2021).

2.2. Defining 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). Open innovation can include both: i) inbound OI, wherein knowledge and resources flow into firms, and ii) 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). In this paper, we focus on the inbound OI, which prior studies suggest is more prevalent than outbound OI (Chesbrough and Crowther, 2006; Michelino et al. 2014).

Traditionally, firms entered into alliances, joint ventures, and partnerships to access external knowledge for innovation. This type of open innovation gained significant traction in the late 1980s and was the focus of several prior studies (e.g., Chan, Kensinger, Keown, and Martin, 1997; Allen and Phillips, 2000; Lerner and Merges, 1998; Gomes-Casseres, Hagedoorn, Jaffe, 2006; Johnson and Houston, 2000). In early 2000s, the rise of the Internet and the emergence of modern web-based platforms and technologies (e.g., Amazon Web Services, Ruby on Rails, Amazon Mechanical Turk, clickworker, and Reddit) have created new forms of open innovation that enabled companies to engage a diverse number of participants through: i) *hackathons* (which bring together individuals to solve ambitious challenges in an extremely limited time frame, e.g., 72 hours or less); ii) *crowdsourcing* and *innovation challenges/contests* (which are open calls to a large, undefined crowd to solicit ideas and feedback to solve a complex task); and iii) *innovation labs* (collaborative, development-focused ecosystems that often involve a dedicated workspace and an internal team who work openly with external partners such as startups, suppliers, innovators, and experts to address corporate challenges and opportunities).

Some real-world examples of these engagements include: i) Netflix, which 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;[4] ii) Capital One, which 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 iii) Liberty Mutual, which opened an innovation hub called Solaris Labs to build and test new products based on emerging trends and customer research.

The new forms of open innovation differ from more traditional ones (e.g., alliances, partnerships, joint ventures) across several dimensions, including the number of participants, the level of control, resource commitment, IP ownership, flexibility, and duration. For instance, traditional forms of open innovation often entail well-defined formal agreements between a limited number of organizations, involve a specific type of partner-firms, are focused on a specific project or market, and are long/medium-term. In contrast, new forms of open innovation typically involve a large number of diverse participants, are less formal, vary significantly in duration (from 72-hour hackathons to long-term open labs), and could involve individuals as well as other firms. We summarize key differences between closed innovation, traditional forms of open innovation, and new forms of open innovation in Appendix C.

2.3. Measuring open innovation

To identify companies that have adopted new forms of open innovation, we rely on articles published in the most common outlets for prior open innovation research, such as *R&D Management*,

[4] https://www.viima.com/blog/open-innovation

Research Policy, Research Technology Management, and *Management Science* (Dahlander and Gann, 2010). Employing content analysis, we identify the most frequently mentioned words used by these studies to describe the implementation of OI strategy. For instance, Chesbrough and Crowther (2006), who survey early OI adopters, use the following strings to identify potential interview candidates: *open innovation, external innovation, sourcing innovation, innovation licensing, technology in-licensing*, *technology licensing, and technology out-licensing*. Noh (2015), who studies open innovation in the manufacturing industry, uses the following keywords to identify firms with OI: *open innovation, collaborative innovation, knowledge sharing, open source, open R & D, open platform, open model, and intellectual cooperation*.

We construct our keyword list to capture: i) broad open innovation strategy *("open innovation", "external technology sourcing", "open R&D")*; ii) discrete short-term OI initiatives *("hackathon", "crowdsourcing", "innovation tournament", "innovation contest")*; and iii) more continuous and longer-term OI initiatives (*"open center", "innovation lab", "open platform," "accelerator"*). We acknowledge that our method may not fully capture all relevant OI engagements and potentially overlooks some OI initiatives. However, doing so would only reduce the power of our tests. Furthermore, we verify that our results are robust if we use a broader set of keywords.[5] We also note that although our focus is on the new forms of open innovation, all our tests include a measure of traditional forms of open innovation (alliances, research collaborations, and joint venture relationships), which is constructed based on the data obtained from FactSet Revere.

Our first 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. An advantage of this measure is that it allows us to identify specific dates of OI engagements to estimate market response to such events. Appendix A provides

[5] Our expanded list of keywords includes "sourcing innovation", "intellectual cooperation", "innovation licensing", "open source", "in-licensing", "technology licensing", "knowledge sharing", "open model", "idea challenge", "idea tournaments", and "innovation challenge", and "incubator".

examples of such news articles. We create our second measure of OI using detailed data from individual-level LinkedIn profiles. 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. An advantage of this measure is that it allows us to capture not only discrete OI events (or their announcements), but also firms' continuous engagement in OI. Appendix A provides examples of such job descriptions.

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 positions and headlines 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% of firms having at least one OI headline, 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., Bernstein, 2015), we conjecture that size may also determine the decision to engage in new OI initiatives. However, the direction of the effect is unclear ex-ante. Small companies can gain a lot by new OI initiatives 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 new OI initiatives. 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 initiatives 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 new OI initiatives, 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 new OI initiatives 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 new OI initiatives are complements or substitutes to traditional 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' new OI initiatives, 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 decision to engage in new OI initiatives 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 initiatives. Similarly, we conjecture that younger CEOs and CEOs with more power might be more likely to engage in OI initiatives. 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, scaled by the total annual number of headlines, respectively. We document that firm size and cash holdings are positively associated with OI initiatives, suggesting that firms are more likely to experiment with OI initiatives when they have greater internal financial resources. Similarly, R&D expense is positively related to OI initiatives, 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). Our results also show a positive relation between new OI initiatives and alliances/joint ventures, suggesting that new OI initiatives are complements to these alternative methods of sourcing knowledge externally. We note that prior performance does not play a role in explaining the engagement in new OI initiatives. Observable CEO characteristics are mostly insignificant.

In Columns 3 and 4, we replace industry fixed effects with firm fixed effects. We observe that several of our variables, e.g., R&D expense, a missing R&D indicator, and cash holdings, become insignificant, suggesting that most of the differences between firms with and without new OI initiatives are absorbed by firm fixed effects. However, alliances/joint ventures continue to predict engagement in new OI initiatives within firm. Furthermore, the coefficients on firm age/size provide some evidence that firms are more likely to engage in new OI initiatives as they mature and grow bigger. To explore this conjecture further, we examine the relation between OI initiatives and firm life cycle and innovation trajectory. We follow Hoberg and Maksimovic (2022) and include four indicator variables for different stages of firm life cycle: Product development, process optimization, product maturity, and product decline. Our results show that firms are more likely to engage in new OI initiatives during process optimization and product maturity stages. We also find a positive relationship between the propensity to engage in new OI initiatives and the number of patents expiring within the next three years, which indicates that firms are more likely to start new OI initiatives when their internal innovation efforts flatten (untabulated). Taken together, this analysis suggests that firms are more likely to turn to external sources of innovation as they mature.

4. Human capital access

Companies typically face the problem of not being able to perfectly observe the quality of prospective employees. New OI initiatives can potentially help overcome this issue as they can allow firms to assess prospective employees' abilities and assess their potential fit with the firm before making the hiring decision. Therefore, enabling firms find individuals that are perfect for the existing job opportunities, instead of selecting a "close enough" fit from inside the company. Furthermore, engaging in public OI initiatives also allows firms to reduce information asymmetry about themselves and provide potential employees information about a firm's less observable characteristics, e.g., culture or technical expertise.

To explore the relation between new forms of OI and a firm's ability to attract talent, we focus on a particularly important subset of employees, i.e., inventors.

4.1. Baseline result

To identify inventor flow, we rely on the USPTO's PatentsView database. Following prior literature, we 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.

In Table 4, we analyze the relationship between OI engagements and inventor inflow (Panel A), inventor exits (Panel B), and inventor net flow (Panel C). In Panel A, the dependent variable is the number of inventors joining the firm at t+1, t+2, and t+3. In Panel B, the dependent variable is the annual number of inventors leaving the firm at t+1, t+2, and t+3, and in Panel C, the dependent variable is the difference between the number of new hires and the number of leavers at t+1, t+2, and t+3. To reduce skewness in the number of inventors, we apply the inverse hyperbolic sine transformation to the dependent variables, 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 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. We also note that because inventor net flow can take on negative values fixed-effects Poisson model, which requires non-negative data, cannot be applied in this setting. We discuss the robustness of our results to alternative model specifications in Section 4.3.1.

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 regression models include the same set of time-variant firm characteristics as used in our earlier analysis of the determinants of new forms 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.

In Panel A, we observe that the within-firm coefficients on both OI measures are positive and significant. 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 observe that OI engagements are also associated with 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. However, the results in Panel C show a significantly positive relation between OI metrics and inventor net flow, suggesting that newly hired inventors outnumber the leaving inventors.

4.2. Robustness

In this section, we discuss several robustness checks of the relation between net inventor flow and new forms of OI initiatives.

4.2.1. 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 re-estimate the baseline regression using two alternative models. Specifically, we use: i) OLS model with the raw number of net inventor flow as the dependent variable (without the inverse hyperbolic sine transformation); ii) scale the raw number of net inventor flow by total number of employees, 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).

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, a culture of openness might be positively correlated with the propensity to engage in new forms of OI and the ability to attract 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 variations in culture (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).

We also use two alternative approaches to measuring the timing of the inventor relocations. First, 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.[6] Second, we re-estimate our measure of inventor flow using a subset of inventors for whom we can track their employment history more precisely using LinkedIn data. Our results are robust to these alternative approaches (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).

4.2.2. 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

[6] 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).

instrument. It is likely that our shift-share instrument does not violate the exclusion restriction because it excludes direct product market peers and 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 6 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. We also repeat all our subsequent tests using a shift-share instrument and document similar results (untabulated). 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.

4.3. GitHub activity

To provide further evidence on the labor market access, 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.[7] Firms can use GitHub for internal and external purposes by creating: i) private repositories, which are accessible only to firm employees and/or ii) public repositories, which are accessible to anyone on the internet. By publicly posting software repositories on GitHub, firms can engage participants from outside firm boundaries and receive crowdsourced feedback on their projects from external developers, including information about the projects' technical potential and the level of public interest. Furthermore, publicly posting software allows firms to establish their presence on GitHub and build their reputation within the tech community.

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 projects they contributed to) and assess the quality of a candidate's actual code and technical abilities. GitHub can also 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.[8]

Although GitHub was launched in 2008, it had very limited activity in the first year of its launch. Hence, we use a six-year window around 2009 to examine the relationship between new forms of OI and labor inflows. We rely on the GitHub Search API to obtain a listing of all organization accounts on the

[7] GitHub was launched in April 2008 and has expanded exponentially in the past decade. 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

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

platform and match them to publicly traded firms in our sample. In this setting, we use public GitHub repositories to proxy for the new forms of OI initiatives. Specifically, we estimate the following regression:

$$\text{Net inventor flow}_{it} = \alpha_t + \beta_i + \gamma X_{it} + \delta \text{GitHub}_i \times \text{Post}_t + \eta \text{Post}_t + \theta \text{GitHubNew}_i + \varepsilon_{it} \quad (1)$$

where $Post_t$ takes the value of one for the period 2009–2011 and zero for the period 2006–2008. $GitHub_i$ 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 neither appeared on GitHub nor engaged in any OI activities during 2006–2011 period. Our variable of interest is the interaction term $GitHub_i \times Post_t$ that reflects the change in inventor flow between firms with and without new forms of OI. Our regression includes the same vector of control variables as used in our earlier analysis, year fixed effects, and firm fixed effects, which subsume the standalone *GitHub* dummy variable.

Table 8 presents estimates of the relationship between GitHub participation and inventor flow. It shows that public GitHub activity is associated with a greater net inflow of inventors. These results are consistent with the proposition that new forms of OI are associated with a greater inflow of talent and provides interesting insights into a labor access in a specific setting. This analysis also complements recent work by Gupta, Nishesh, and Simintzi (2025) who use GitHub's 2016 policy change to show that a reduction in the information asymmetry about employee productivity enhances large firms' access to labor capital.[9] However, given that the decision to adopt GitHub will always be endogenous, these results similarly reflect correlations and not causation.

4.4. Inventor productivity and innovation

Although our results show a positive relationship between OI initiatives and net inventor flow, an increase in the number of inventors does not necessarily imply that OI initiatives are beneficial. For instance, newly hired inventors might be less qualified than the departing ones. Even if OI engagements help attract

[9] Before 2016, users could only display contributions they made to public GitHub repositories on their profiles. In 2016, GitHub introduced the option for users to include their previously hidden (anonymized) private contributions, which further reduced information asymmetry about users' skills.

more talented inventors, these initiatives can reduce incumbent inventors' incentives to innovate within the existing firm and curb in-house creativity. Furthermore, increased inventor turnover can be very disruptive for inventor teams and might have negative effects on innovation. To test these conjectures, we compare the productivity of newly hired and leaving inventors and analyze the relationship between OI initiatives and firms' subsequent innovation quantity and quality.

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).[10] 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 7, respectively. We observe that newly hired inventors compare favorably to leaving inventors, as the coefficients on OI measures are positive.

To examine the relationship between OI and the overall quantity of innovation, we rely on patents because innovations are usually officially introduced to the public in the form of approved patents. 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 8 is the number of patent applications at t+1, t+2, and t+3. Similar to our earlier analysis, we apply the inverse hyperbolic sine transformation to the dependent

[10] 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.

variables to account for the right-skewness in the distribution of patent grants. Our results, however, are robust to fixed-effects Posson estimations. The results indicate that bot OI metrics are positively related to the volume of innovative output.

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). 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 in Panels B and C reveals that OI initiatives are positively related not only to the quantity of innovation output but also to the quality of innovation.

In Panels D and E of Table 8, 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.[11]

5. OI and firm value

Our earlier results suggest a positive relation between OI initiatives and inventor inflow and innovation outcomes. However, OI engagements may still fail to deliver meaningful value, as they come with the risk of leaking confidential information to competitors and losing control over the company's intellectual property. Furthermore, managing relationships with a diverse range of external partners can be

[11] 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).

challenging and the increased coordination costs might render OI initiatives value-decreasing. In this section, we examine whether OI engagements have any meaningful effect on firm value, by analyzing the announcement returns surrounding OI initiatives and exploring the relation between OI and several metrics of operating performance.

5.1. OI announcement returns

To examine whether the benefits of new OI initiatives outweigh the costs, we analyze announcement returns surrounding new OI initiatives identified from the news articles. 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 initiative announcement date.

Table 9 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. The magnitude of stock price reactions to the new forms of OI is comparable to stock price reactions to patents that were likely an outcome of closed innovation, i.e., patents announced prior to the onset of new forms of OI. For instance, Houston and Roskelley (2024) document average returns of 0.12% over [-1:+1] window for the period 1980–2001. However, the magnitude of stock reaction to new forms of OI is smaller than returns to more traditional forms of OI, e.g., mean one-day CAR of 0.64% for alliances over the period 1983–1992 (Chan et al., 1997) and mean two-day CAR of 0.74% for joint ventures over the period 1972–1979 (McConnell and Nantell, 1985). This is not surprising given that the traditional forms of OI are, on average, longer term and less frequent. We also estimate separately market response to: i) shorter-term engagements, such as tournaments and hackathons, and ii) longer-term engagements, such as open innovation labs and accelerators. We observe a positive market response to both types of OI, with the market reaction to longer-term engagements significantly larger in two out of three event windows (untabulated).

A potential concern that one might have is that our estimates of investors' reactions to OI might reflect market response to other contemporaneous news. To rule out this possibility, we omit OI engagements that are potentially contaminated by other confounding events, such as dividend payments, dividend announcements, merger announcements, earnings restatements, or other R&D related announcements that occur within +/- 5 days of the OI engagements. In addition, 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. We also examine whether OI announcements are preceded by a significant pre-announcement price run-up over the [-10:-4] window and do not find any evidence that firms time OI announcements following other good news (untabulated).

5.2. 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.

Innovation work and new product development processes take time. An open approach can accelerate the innovation process and reduce the time to market (Chesbrough, 2006). If new forms of OI enable 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 A of Table 10 by splitting the sample into firms that operate in high-tech industries[12] and those that do not. We observe that although the market reaction is positive in both sub-samples, the magnitudes are larger for

[12] 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.

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 new forms of OI are 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 become critical. If the companies that can innovate faster are more likely to gain a competitive advantage, we expect that the positive reaction to new OI initiatives 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 new OI engagements can be especially detrimental in more competitive industries, suggesting a lower response to new OI initiatives 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 B of Table 10 reports CARs for firms operating in more (less) 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. Firms operating in environments wherein it is easier to hire the participants of OI initiatives might benefit more from these forms of OI. Alternatively, new OI strategies, such as crowdsourcing, might be particularly valuable in labor-constrained environments. 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 C of Table 10 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 new OI engagements are more likely to materialize when firms can recruit qualified workers with relevant experience.

5.3. Cost reduction and sales growth

Our results documenting a positive market response to OI initiatives suggest that, on average, these engagements are value-enhancing. In this section, we examine whether utilizing external sources of innovation contributes to firm value by stimulating growth or reducing costs. New forms of 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). Alternatively, firms may use new forms of 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 examine the relation between OI engagements and 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.

In Table 12, we analyze the relation between OI engagements 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 OI engagements predict sales growth or introduction of new products. Taken together, our analysis suggests that firms are more likely to use new forms of OI for defensive reasons (decreasing costs and risks).

6. Conclusion

Firms have increasingly attempted to improve their performance by tapping into sources of external knowledge (Chesbrough, 2003; 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. 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 new forms of OI from news articles and job descriptions, we find that OI engagements are associated with the reshuffling of inventors, wherein more productive inventors join these firms, and a higher level and quality of innovation output. OI initiatives, on average, are value-increasing. Furthermore, our results suggest that new forms of OI are more likely to be used to improve efficiency and cut costs.

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 initiatives. 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-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; 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 has focused on the implications of OI initiatives for focal firms. 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.

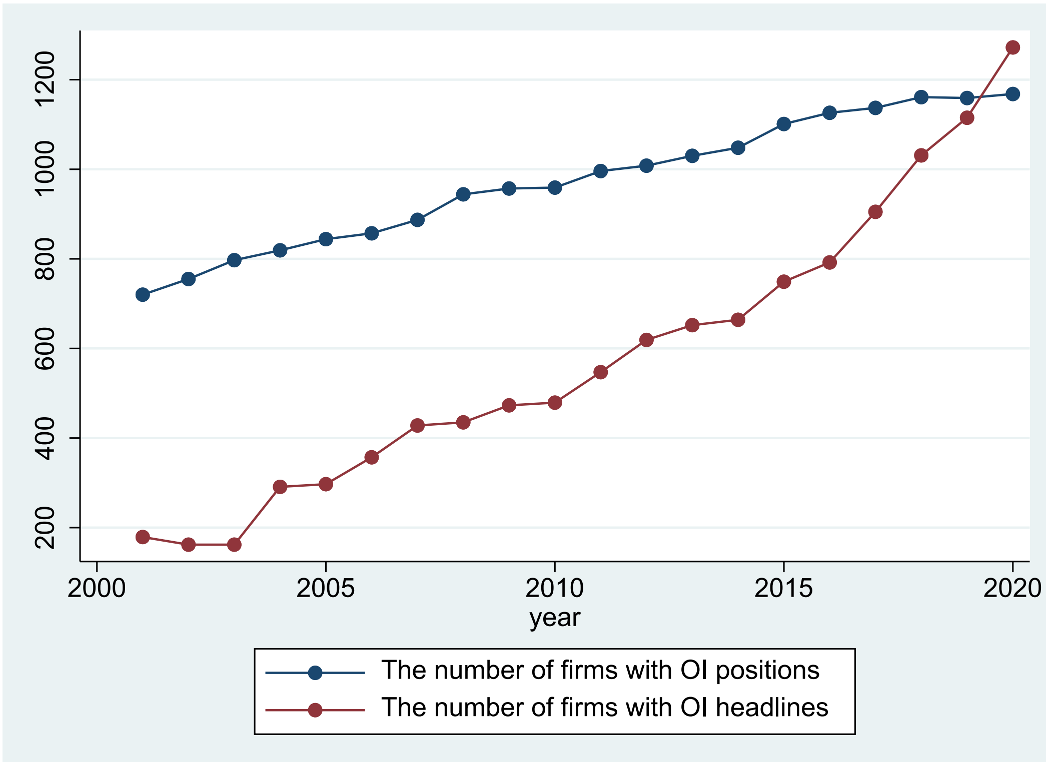

Table 1. Descriptive statistics

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)
Dependent variables					
New hires	12.28	89.64	0.00	0.00	1.00
Leavers	4.91	37.79	0.00	0.00	1.00
Net inventor flow	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
# of patents	14.37	57.96	0.00	0.00	3.00
Citations	123.04	539.47	0.00	0.00	9.00
Patent economic value	1083.12	5468.20	6.88	39.28	263.40
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
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
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 initiatives

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 initiatives 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 initiatives

	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. 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 inventor flow

	Net inventor flow					
	***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 5. 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. $GitHub_i$ 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 neither appeared on GitHub nor engaged in any OI activities during 2007–2011 period. 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 inventor flow		
	***t*+1**	***t*+2**	***t*+3**
	(1)	**(2)**	**(3)**
GitHub × Post	0.138**	0.116*	-0.016
	(2.34)	(1.90)	(-0.23)
Firm and CEO characteristics	Yes	Yes	Yes
Firm and year fixed effects	Yes	Yes	Yes
Number of observations	4,553	4,234	3,977
Adjusted R-squared	0.726	0.715	0.718

Table 6. Robustness

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 inventor flow					
	***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 7. 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 8. Innovation quantity, quality, 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: Citations

	Citations					
	***t*+1**	***t*+2**	***t*+3**	***t*+1**	***t*+2**	***t*+3**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Ln (% of OI positions)	0.094**	0.099***	0.104***			
	(2.55)	(3.44)	(3.42)			
Ln (# of OI headlines)				0.060***	0.091***	0.089***
				(2.41)	(4.47)	(4.20)
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	30,413	30,413	30,413	30,413	30,413
Adjusted R-squared	0.822	0.845	0.843	0.822	0.845	0.843

Panel C: Economic value

	Patent economic value					
	t+1	*t*+2	*t*+3	*t*+1	*t*+2	*t*+3
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Ln (% of OI positions)	0.045* (1.88)	0.058** (2.31)	0.060** (2.29)			
Ln (# of OI headlines)				0.095*** (5.42)	0.083*** (4.89)	0.082*** (4.23)
Firm and CEO characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firm and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	11,972	9,573	7,627	11,972	9,573	7,627
Adjusted R-squared	0.907	0.910	0.914	0.908	0.910	0.914

Panel D: 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*** (2.81)	0.138*** (3.54)	0.144*** (3.44)			
Ln (# of OI headlines)				0.120*** (3.14)	0.169*** (4.19)	0.173*** (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 E: 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 9. 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.

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

Table 10. Cross-sectional variation

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: 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 B: 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 C: 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 11. Cost reduction

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. Sales growth

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.
New hires	The number of a firm's newly hired inventors in a given year.
Leavers	The number of a firm's inventors who leave for other firms in a given year.
Net inventor flow	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.
# of patents	The number of patent applications filed in a given year.
Citations	Total number of lifetime citations received by the patents applied for by a firm in a given year.
Patent economic value	Patent value metric as measured by Kogan et al. (2017).
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.
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.
COGS	Cost of goods sold.
Sales growth	Annual sales growth.
New products	Annual number of new products.
	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.

Appendix B: Variable definitions *(continued)*

Panel B: Firm characteristics (continued)	
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.

Appendix C: Comparison of different types of innovation strategies

	Closed innovation	Joint Ventures/ Alliances/ Partnerships	Corporate Venture Capital	Open Innovation
Knowledge sourcing	Internal only	Internal & External	Internal & External	Internal & External
Visibility	**Low:** not visible to outsiders	**Medium:** Might be announced publicly	**Low:** not visible to outsiders	**Very High**: intentionally public
Number of participants	**Low:** One company	**Low:** Typically, two or more companies	**Low:** Typically, two or more companies	**Very High**: Unlimited
Formality	**Low:**	**High:** formalized agreements	**High:** formalized agreements	**Low:** Flexible, varied collaborations
Scope	**Broad:** variety of projects	**Narrow:** specific project or market entry	**Narrow:** specific project or market entry	**Broad:** variety of projects
Level of control	**High:** Full control over process, IP, and direction.	**High:** Shared among partners according to a formal governance structure.	**Moderate:** Control is limited to shareholder rights and often a board seat.	**Low to Moderate:** Host controls the process, but not the generation of ideas.
Resource commitment	**Very high & fixed**: Requires sustained, significant investment in salaries, facilities, and overhead	**High & shared**: Large capital commitment, but costs and risks are shared among partners.	**Moderate & variable**: Investment size varies, but requires a dedicated fund and management team.	**Low & flexible:** Costs can be scaled from a small prize for a contest to a larger lab budget.
IP ownership	**Full:** Full ownership	**Joint:** Shared ownership	**Indirect:** Indirect ownership via equity stake in startup	**Varies**: can be host-owned, participant-owned, or licensed.
Flexibility	**Low:** Long-term projects and fixed assets create high inertia.	**Low:** Less flexible due to legal and equity structures.	**Moderate:** Can invest in and divest from startups relatively easily.	**Very High:** Can run short-term initiatives with low commitment. Can chose to adopt only successful ideas.
Duration	**Long:** Perpetual	**Medium:** On average 7 years.	**Medium:** Typically, 4-10 years.	**Varies:** Can be very short (<72 hours) or long-term.