ESSAYS IN CORPORATE FINANCE AND CORPORATE INNOVATION

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A Dissertation submitted to the Faculty of Graduate Studies in partial fulfillment of the requirements for the degree of Doctor of Philosophy

Graduate Program in Business Administration

Schulich School of Business, York University

Toronto Ontario

September 2023.

Abstract

In the first chapter I investigate whether all firms grant stock options to rank-and-file employees (RFOs) for retention purposes. I find that it depends on their level of investment in intellectual property. Firms grant more RFOs if they have more knowledge capital, more patents awarded, more citations received by these patents, and more patents for "breakthrough" innovations. After the risk of poaching by rival firms is diminished by the adoption of the Inevitable Disclosure Doctrine, I find that firms with above median level of knowledge capital reduce their RFO grants by 32% relative to control firms; the reduction is minimal for firms with below median level of knowledge capital.

In the second chapter I investigate how effective are rank-and-file option (RFO) grants in retaining employees. Previous studies find that while there is an initial reduction in employee turnover, the effect is temporary and quickly reversed within three years of the option grants. In this chapter, I focus on inventor retention and find that the impact of RFOs is permanent. I find that there is a 36% reduction in inventor turnover in the year of grant and the impact remains over the next three years. More importantly, there is no reversal of the effect suggesting that the benefit is permanent instead of transitory. I also find that the importance of RFOs to reduce inventor turnover increases following the implementation of FAS123R when firms drastically reduce the use of RFO grants.

In the final chapter I study the behavior of firms with respect to their patent applications. I find that firms engage in window dressing by timing the date of their patent applications. I find that almost 40% of firms' yearly patents are filed in the last quarter of the calendar year accompanied by a parallel reduction in the quality of these patents. The behavior is more prevalent

among firms subject to lower external and internal monitoring, supporting the incentive to window dress as the underlying channel. To establish window dressing as the key mechanism behind this behavior, I use the adoption of America Invents Act as a quasi-natural experiment that has increased the costs of window dressing. Following the adoption of the Act, the window dressing behavior become less prevalent providing support for my window dressing argument.

Acknowledgements

First, I would like to thank my supervisor, Yisong Tian, and my committee members, Kee-Hong Bae and Mark Kamstra, for all their help, advice and patience throughout the completion of this dissertation. I am also grateful to my co-author, Alireza Mahalati, for his help and support during our work together. A special thanks goes to Yisong Tian, Lilian Ng and Ambrus Kecskes for the financial support through the various teaching, grading and assistantship opportunities they provided. Lastly, the advice and feedback provided by the remaining Finance faculty members at the Schulich School of Business has been invaluable in the ultimate completion of this dissertation.

Contents

Chapter I

I Corporate innovation, intellectual property, and rank-and-file stock option grants

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1 Introduction

Stock options have been widely used as managerial equity incentives, aligning the interests of top executives with those of the shareholders. This practice is supported by the agency theory of the firm in an optimal risk-sharing framework (Holmstrom,1979; Jensen and Murphy, 1990). In comparison, incentive alignment is not a good explanation for the widespread use of stock option grants for rank-and-file employees (RFOs) due to the well-known dead-weight cost and free-rider problem (Bergman and Jenter, 2007). While the action of any employee below the executive rank has little impact on stock price, the positive correlation between the stock price and the employee's human capital creates discount to the value of these RFOs.

So why do firms grant RFOs to their employees? Previous studies suggest that employee retention is a plausible motive. Due to vesting requirements, employees forfeit their stock options if they leave for a competitor before the options are vested. The value of stock options is also positively correlated with industry-wide performance, making their forfeiture even more costly exactly when the employee's outside employment opportunities are more plentiful. RFOs are thus a form of delayed compensation that is indexed to outside employment opportunities, helping to retain employees when such outside opportunities become more available (Oyer, 2004; Oyer and

Schaefer, 2005). There is indeed evidence that firms grant more stock options to rank-and-file employees when they have more outside opportunities in the local labor market (Kedia and Rajgopal, 2007; Lee, Thorburn and Xu, 2021).

If employee retention is the primary motive for granting RFOs, then why do some firms use them extensively while others barely use them at all? While the top 25% of firms in my sample provide more than $11 million worth of stock options a year to their rank-and-file employees, the bottom 25% provide less than $10,000's worth. What could be behind such variations in the practice across firms? Even for firms that do grant RFOs regularly, how do they allocate them among their rank-and-file employees? Do they target a subset of key employees or treat everyone equally? This is highly relevant because the average amount of stock options granted to a rank-and-file employee per year is less than $1,000. It is unlikely to be an effective retention tool if RFO grants are shared equally among all rank-and-file employees. In this chapter, I fill this gap in the literature by focusing on the development and protection of intellectual property and show that a firm's use of RFOs is closely tied to its investment in intellectual property. I provide evidence that firms with more ownership of intellectual property grant more RFOs and they target their RFO grants to the subset of employees involved in the research and development of intellectual property.

To quantify intellectual property, I focus on a firm's research and development (R&D) program as most firms develop their intellectual property, such as the acquisition of patents and other proprietary rights (e.g., brands, trademarks or copyrights), via such programs. I use a firm's investment in the R&D program, as measured by *knowledge capital*, and the output of such programs, as measured by a firm's patent portfolio, as proxies for intellectual property and study how the use of RFOs is tied to these proxies.

I first show that the use of RFOs is positively associated with a firm's level of *knowledge capital* but uncorrelated with its level of *organization capital*. Knowledge capital is the capitalization of R&D expenditures and accounts for a firm's cumulative investments in intellectual property. In comparison, organization capital is the capitalization of selling, general and administrative (SG&A) expenses and accounts for a firm's cumulative investments in employee training, brand, customer relationships and distribution systems (Peters and Taylor, 2017). The positive correlation between the use of RFOs and knowledge capital suggests that firms grant more RFOs if they invest more in the research and development of intellectual property. The absence of any relationship between RFOs and organization capital also suggests that firms might be using RFOs as a retention tool for attracting and retaining those employees who are involved in the research and development of intellectual property instead of other employees. If firms are concerned about the cost of employee turnovers, they do not appear to treat all employee turnovers equally; instead, they seem to target RFO grants to a subset of key employees involved in R&D programs.

Of course, a firm's investment in knowledge capital is only a measure of the resources the firm has devoted to the research and development of intellectual property. It does not capture the productivity or output of that investment. Without a measure for that output, we do not know if a firm actually has any intellectual property to protect, irrespective of how much resources it has deployed for it. To measure that output, I focus on the firm's patent portfolio and use the number of patents received each year and their citation counts as proxy for the quantity and quality of that output, respectively. Consistent with expectations, I find a positive relationship between the use of RFOs and the accumulation of intellectual property as proxied by a firm's patent portfolio. In particular, the size of a firm's annual RFO grant is positively related to the total number of patents granted that year and the total citation counts received by these patents (over the next five years). In both cases, the relationship is statistically significant at the 1% level. This is further confirmation that a key motive for the use of RFOs is the recruiting and retention of inventors who are involved in the research and development of intellectual property as proxied by the number of patents awarded and their citation counts. RFO grants reward inventors for their past performance and help retain them for their expected future contributions.

To further identify the precise mechanism of using RFOs for employee retention purposes, I distinguish two types of intellectual property – patents classified as either *incremental* or *breakthrough* innovations. Although all innovations are potentially valuable to the firm, breakthrough innovations create more value than incremental innovations do (Hall, Jaffe and Trajtenberg, 2005; Kogan et al., 2017). Incremental innovations are generally associated with the exploration of existing ideas and technologies that are already familiar to the inventors. They require less resources in terms of the firm's R&D budget and inventors' time. These efforts are expected to produce more predictive outcomes and create incremental improvement to existing technology. In comparison, breakthrough innovations are associated with the exploration of unknown ideas or areas of technology that are beyond the inventors' expertise or unrelated to their past innovations. They generally require much more corporate resources and may take much longer time to develop. Investment in the development of this type of innovations is highly risky in the sense that it may lead to disruptive innovations or fail spectacularly without any breakthrough at all. Between these two types of innovations, it is clear that inventors of breakthrough innovations require more protection against poaching by rival firms in comparison with inventors of incremental innovations. I thus expect firms to use more RFOs when more breakthrough innovations are produced by the firm's R&D program.

To differentiate breakthrough innovations from incremental innovations, I rely on several commonly used patent measures in previous studies (e.g., Balsmeier, Fleming and Manso, 2017; Gao, Hsu and Li, 2018; Acemoglu, Akcigit and Ceilk, 2020; Byun, Oh and Xia, 2020; Lin, Liu and Manso, 2020). While *Unknown Patents* and *Top10%Citations* are proxies for breakthrough innovations, *Known Patents* and *Bottom90%Citations* are proxies for incremental innovations. A known (unknown) patent is a patent that is filed in technology classes that the firm has (not) received patents previously, thus more likely to be associated with an incremental (a breakthrough) innovation. *Known Patents* and *Unknown Patents* are simply the counts of these patents that a firm is awarded each year, respectively. Likewise, patents among the top 10 percent of the citation distribution of all patents granted in the same year are more likely to be breakthrough innovations due to their recognition by other inventors. Counting only these highly cited patents gives me another proxy for breakthrough innovations (*Top10%Citations*). The remaining patents (below the top 10 percent of the citation distribution) are considered less disruptive, and the total number of these patents is a proxy for incremental innovations (*Bottom90%Citations*).[1]

Consistent with expectations, I find that the use of RFOs has a much stronger relationship with a firm's patents classified as breakthrough innovations than it has with those classified as incremental innovations. I find that the use of RFOs has a strong positive relationship with *Top10%Citations* but no relationship at all with *Bottom90%Citations*. Such contrasting relationships suggest that firms target RFO grants for the subset of employees who are involved in the development of breakthrough innovations (*Top10%Citations*) as opposed to incremental innovations (*Bottom90%Citations*). Similar results are obtained if I use *Known Patents* and

[1] I also use other percentiles such 85% and 95% as cutoff for the definition of breakthrough vs. incremental innovations. The results are not materially different.

Unknown Patents as proxy for incremental and breakthrough innovations, respectively. The only difference is that the use of RFOs is positively related to both *Unknown Patents* and *Known Patents*. The relationship is however roughly four times as strong for *Unknown Patents* than for *Known Patents* and the difference is statistically significant at the 1% level. These findings suggest that firms are more concerned with losing their "superstar" inventors who are involved in the development of breakthrough innovations; these firms increase the use of RFOs in the presence of such "superstar" inventors. Establishing a linkage between the use of RFOs and patents, especially those classified as breakthrough innovations, is quite important. It provides further evidence that the development and protection of intellectual property is the primary reason that firms use RFOs for employee retention purposes.

The close link between RFO grants and a firm's intellectual property suggests that firms appear to use RFOs for the purpose of attracting and retaining key personnel involved in the research and development of intellectual property such as patents. Nevertheless, we should not ignore alternative explanations for the documented positive relationship. It is also possible that omitted variables or reverse causality could be behind the phenomenon. While I do control for firm characteristics (e.g., firm size, leverage, valuation, stock return volatility, and marginal tax rate), industry and year fixed effects in my regression analysis, further tests are needed to ensure that my results are not due to omitted variables or other endogeneity concerns.

One alternative explanation is that RFO grants are part of the firm's overall compensation policies, influenced by various factors such as agency problems, corporate investment policies and financing decisions. As a result, the board has adopted the same option granting policy for all employees of the firm. If that is the case, I should find a parallel relationship between stock options granted to the CEO and intellectual property. If such a parallel relationship is indeed present, then it is likely that the use of RFOs is more than just for the development and protection of intellectual property. Empirically, I find no relationship at all between the CEO's annual option grants and patents received by the firm each year (either in the total number of patents awarded or their citation counts). This is consistent with the idea that firms are more likely to link the CEO's stock option grants to the firm's overall performance as opposed to its progress in technological innovation. The same results hold if I examine the relationship between options granted to other top executives and patents received by the firm. These findings support the conjecture that firms have a different motive for granting RFOs than for granting options to their CEOs and other top executives.

Another possible explanation for the documented positive relationship between the use of RFOs and intellectual property is that there is an unknown factor driving the variations of both variables. For example, firms could simply follow the practice of industry leaders when setting their own policies on R&D spending and RFO grants. Perhaps, these leading firms invest more heavily in R&D programs in order to maintain their leadership position in the industry. To finance the higher R&D expenditure, these firms may use more RFO grants to supplement cash expenditure in order to conserve limited financial resources for other corporate spending. If that is the case, the positive relationship is simply the result of herding and thus may have little to do with the use of RFOs for employee retention purposes.

To address such endogeneity concerns, I utilize a quasi-natural experiment based on the adoption and rejection of the Inevitable Disclosure Doctrine (IDD) by the US state courts. The IDD is a legal doctrine that is designed to prevent the poaching of key personnel by rival firms and protect against the "inevitable" disclosure of proprietary information and trade secrets by the departing employees. If a state recognizes the IDD doctrine, all firms in that state would enjoy the protection even if the employee does not sign a noncompete or nondisclosure agreement with the firm or if the employee leaves for another firm outside the state. Because the timing of adoption (and rejection) of the IDD varies across states,[2] it allows for difference-in-differences tests that help to examine the impact of the exogenous IDD adoption/rejection event on the relationship between the use of RFOs and intellectual property. This exogenous external shock provides an opportunity to circumvent the potential endogeneity concerns surrounding this relationship.

Empirically, I regress the size of a firm's annual RFO grant (scaled by shares outstanding) on the IDD dummy (1 if the firm is located in a state that the IDD is in effect in that year and 0 otherwise), a proxy for intellectual property (IP), a dummy variable for firms with a high level of intellectual property ($HIGH_{IP}$), the interaction term $IDD \times HIGH_{IP}$, and control variables. Variables used as proxy for a firm's intellectual property include *Knowledge Capital*, *Total Patents* and *Total Citations*. The dummy variable for high intellectual property ($HIGH_{IP}$) is 1 if the firm's intellectual property is above the median level of all firms in the sample and 0 otherwise. If firms use RFOs primarily for employee retention purposes, I expect them to reduce RFO grants after the recognition of the IDD by the state courts in the firm's state, especially for firms with a high level of intellectual property. In contrast, if firms use RFOs for other reasons such as herding described previously, the recognition of the IDD should have no impact on the practice.

Results of these regressions support the employee retention hypothesis but only for firms with a high level of intellectual property. When the IDD dummy is included in the regression without any proxy variable for intellectual property nor its interaction terms, the coefficient of the IDD dummy is negative but not statistically significant. This is consistent with a reduction in the

[2] For example, Florida adopted it in 1960 but rejected it in 2001 while Texas adopted it in 1993 and then rejected it in 2003.

use of RFOs after the adoption of the IDD in comparison with control firms in states without the IDD doctrine. Nevertheless, it only provides weak support for the employee retention hypothesis as the size of the reduction is not particularly large for the full sample. It does not mean, however, that firms do not use RFOs for employee retention purposes. It is possible that only some firms grant RFOs for retention purposes while others do not, leading to a relative weak outcome in aggregate.

To further explore such a possibility, I add several variables to the regression including a proxy for intellectual property (IP), a dummy variable for firms with a high level of intellectual property ($HIGH_{IP}$) and the interaction term $IDD \times HIGH_{IP}$. In this specification, the coefficient of the IDD dummy measures the impact of the IDD adoption on the use of RFOs for firms with above median level of intellectual property (relative to control firms without the IDD protection). In comparison, the coefficient of the interaction term $IDD \times HIGH_{IP}$ measures the difference in the impact of the IDD adoption between firms with above and below median level of intellectual property. If the adoption of the IDD has no impact on a firm's use of RFO grants, both coefficients should be close to zero and statistically insignificant.

Results of these regressions show that the coefficient of the IDD dummy is always small and statistically insignificant regardless of the proxy used for intellectual property (either *Knowledge Capital*, *Total Patents* or *Total Citations*). This is clear evidence that firms with below median level of intellectual property do not reduce their use of RFOs after the adoption of the IDD by the state courts in comparison with control firms in states that do not recognize the IDD. These firms thus do not appear to use RFOs for employee retention purposes. In contrast, the coefficient of the interaction term $IDD \times HIGH_{IP}$ is consistently negative and statistically significant at the 1% level. The coefficient is also fairly large in magnitude, varying within a close range from –0.57 to

–0.59, depending on which proxy for intellectual property is used. Relative to control firms in states that do not recognize the IDD, firms with above median level of intellectual property reduce their use of RFOs per year by an amount equivalent to 0.6% of shares outstanding more than their counterparts with below median level of intellectual property after the recognition of the IDD by the state courts. As the size of a typical firm's annual RFO grants is equivalent to 0.76% of shares outstanding (based on sample median), the difference in reduction is roughly 76.3% more for firms with a high level of intellectual property than it is for their counterparts. This level of difference is clearly very large and economically substantial. After the recognition of the IDD by the state courts, firms do reduce their use of RFOs but only for firms with a high level of intellectual property. Firms with a below median level of intellectual property do not reduce their use of RFOs at all relative to control firms in states that do not recognize the IDD. These findings suggest that not all firms use RFOs for employee retention purposes. Only firms with a high level of intellectual property do.

In addition, the adoption of the IDD has little impact on a firm's investment in intellectual property (as proxied by *Knowledge Capital*, *Total Patents* or *Total Citations*). This is not entirely surprising because investment in intellectual property is important for value creation in the long run. The external protection against poaching via the recognition of the IDD by the state courts does not change that importance. While the firm might save on the resources previously used for protection against poaching, that saving does not necessarily reduce the value of investments in technological or other innovations. This further confirms that the IDD adoption is indeed an exogenous external shock and does not systematically impact a firm's investments in intellectual property.[3]

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[3] I also find that the adoption of the IDD has no impact at all on organization capital, contrary to Qiu and Wang (2018) who find a positive impact. This is likely due to differences in sample period between the two studies. I verify that

The wage indexation theory of Oyer (2004) and Oyer and Schaefer (2005) is another alternative explanation for the documented positive relationship. RFO grants help firms to retain employees because it allows them to index their employees' deferred compensation to outside employment opportunities which are typically found in geographically nearby firms. Indeed, Kedia and Rajgopal (2007) and Lee, Thorburn and Xu (2021) find evidence that firms grant more RFOs when their employees have more outside opportunities in the local labor market. Does the wage indexation phenomenon also explain the relationship between the use of RFOs and corporate innovation documented here? I confirm that wage indexation does explain a fraction of the positive relationship. Even though the use of RFOs is highly influenced by the level of their use by neighboring firms, RFO grants are still highly correlated with technological innovations (both breakthrough and incremental innovations) even after controlling for the use of RFOs by nearby firms. Consequently, wage indexation theory alone does not fully explain the use of RFOs by corporations.

My work is closely related to two contemporary studies by Lie and Que (2020) and Lee, Thorburn and Xu (2021). Both studies use the adoption and rejection of the IDD as a quasi-natural experiment to examine how the recognition of the IDD by state courts impacts the use of RFOs. Lie and Que (2020) show that firms reduce their use of RFOs after the adoption of the IDD. They interpret it as evidence that firms use RFOs as an employee retention tool. Lee, Thorburn and Xu (2021) show that firms grant more RFOs when their employees have greater outside employment opportunities, establishing a motive for using RFOs as an employee retention tool. They further

there is indeed a positive impact if I use their sample period of 1960-1994; it disappears if my sample period of 1992-2014 is used.

show that the relationship is weakened after the recognition of the IDD by the state in which the firm is located. The protection of the IDD reduces the need for the use of RFOs as a retention tool.

My study complements theirs by identifying the precise mechanism firms use RFOs as an employee retention tool. I show that not all firms use RFOs for employee retention purposes. In fact, half of the firms in my sample appear not to do so at all. Only firms that have above median level of investment in intellectual property do. After the recognition of the IDD by the state courts, only firms with above median level of intellectual property reduce their use of RFOs in comparison to control firms in states that do not recognize the IDD. Even with the external protection against poaching by rival firms provided by the IDD doctrine, firms with below median level of intellectual property maintain the same level of RFO grants relative to control firms. This is evidence against the hypothesis that these firms use RFOs for employee retention purposes.

My results are also consistent with the premise that firms target a key subset of employees when they do use RFOs for employee retention purposes. These are employees who are involved in the research and development of intellectual property. The use of RFOs is positively related to a firm's investment in knowledge capital but not organization capital. This is an important distinction as knowledge capital is more closely related to the investment in technological innovations while organization capital is more closely related to employee training, brand, customer relations and distribution systems. I further establish a positive relationship between the use of RFOs and patents awarded to the firm each year and their citation count, driven mostly by patents classified as breakthrough innovations as opposed to incremental innovations. These findings support the hypothesis that the recruiting and retention of inventors, especially "superstar" inventors, is the most likely motive for granting stock options to rank-and-file employees.

The rest of the chapter proceeds as follows. Section 2 describes the sample of firms and provides descriptive statistics of their characteristics, investments in intangible capital and technological innovations, and their use of RFOs. In Section 3, I describe my empirical methodology and details of the empirical tests. In Section 4, I empirically investigate the relationship between the use of RFOs and a firm's investment in intellectual property. Section 5 provide additional tests and robustness checks. The final section concludes.

2 Data and descriptive statistics

2.1 Rank-and-file stock option grants

My sample includes all firms covered by the Standard and Poors' ExecuComp database from 1992 to 2015. Although more recent data is available, I choose 2015 as my last year in the sample because I need another five years afterwards to accumulate sufficient citation data for patents granted that year and the patent data I use ends in 2015[4]. After excluding firms in the utility and financial industries (with two-digit SIC codes of 49 and 60-69 inclusive), I have a total of 35,068 firm-year observations. As firms do not report the number of RFOs granted each year, I infer this number from the total number of options granted to all employees and the total number of options granted to the top five executives (e.g., Oyer and Schaefer, 2005; Kedia and Rajgopal, 2009; Call, Kedia and Rajgopal, 2016).

[4] I use the patent data constructed from the USPTO by researchers at *Duke University* as described by Arora, Belenzon and Sheer (2022). Their extension to the commonly used NBER patent data (Hall, Jaffe and Trajtenberg, 2001; Bessen, 2009) improves the matching of assignees (name of company filing the patent) and Compustat firms by addressing name changes and ownership changes. For robustness, I also repeat all empirical tests using the NBER patent data and find no material change in any of my results.

In extracting data for each year's RFOs, adjustments are made due to a change in the way firms report stock option grants during my sample period. During the period between 1992 and 2006, firms report stock option grants under the so-called "old" reporting format (e.g., Cole, Daniel and Naveen, 2006). Under this format, firms not only report the number of stock options granted to each top executive for the fiscal year but also these options as a fraction of all options granted to all employees by the firm (variable PCTTOTOPT). This allows for an accurate tabulation of stock options granted to the CEO, other top executives, and all options granted by the firm. Subtracting the options granted to top executives from all options granted by the firm, I have a proxy for the number of RFOs granted in each fiscal year.

During the period between 2007 and 2015, firms report stock option grants under the "new" reporting format mandated by the Financial Accounting Standard Board under FAS123R. Although more details of stock option grants are disclosed, firms no longer report each executive's option grants as a fraction of all options granted by the firm. In this case, I rely on Compustat to find the total number of options granted (variable OPTGR) by the firm in each fiscal year (Kedia and Rajgopal, 2009; Call, Kedia and Rajgopal, 2016). From this total option grant figure, I calculate RFOs as before by subtracting out stock options granted to top executives. To make sure this approach is valid, I recalculate RFOs during the period between 1992 and 2006 using Compustat's OPTGR and compare with the number calculated using ExecuComp's PCTTOTOPT. The two numbers of RFOs match nearly perfectly, supporting the use of Compustat's OPTGR for total number of options granted by the firm in a fiscal year.

Similar to Kedia and Rajgopal (2009), I normalize RFOs granted each year by the total shares outstanding, which facilitates a more meaningful comparison among firms of different sizes. The same treatment is applied to stock options granted to the CEO and other top executives in my comparative analysis and robustness checks. As shown in Panel A of Table 1, firms in my sample grant an average of $14.6 million of RFOs each year, which is roughly equivalent to 2.0% of shares outstanding (if exercised). The median figures are $3.7 million and 0.8%, respectively. In comparison, CEOs get an average (a median) of $1.3 (0.3) million of stock options each year, representing 0.24% (0.04%) of shares outstanding. The distribution of stock option grants across firm-years is clearly skewed. In subsequent analysis, I thus winsorize both option grant figures at the 99% and 1%, in order to minimize the impact of outliers.

Table 1

2.2 Corporate innovation and intellectual property

Corporate innovation is crucial for a firm's long-term success, especially for firms operating in a highly competitive environment. Such innovation could involve the development of new products, new features, new markets, new operational processes, a new business model or other aspects of business operations. As corporate innovation is difficult to quantify, I focus on intellectual property which is a subset of corporate innovations that is observable and much easier to quantify empirically. By some estimate, intellectual property accounts for more than 30 percent of the aggregate market value of publicly traded firms in the U.S. (e.g., Shapiro and Hassett, 2005). It is thus reasonable to use intellectual property as a proxy for corporate innovation.

I measure a firm's investment in intellectual property in two ways, capturing both the input and output of such investment. The first measure is the level of investment (i.e., input) in knowledge capital via the capitalization of R&D expenditures (e.g., Chan, Lakonishok and Sougiannis, 2001; Hirshleifer, Hsu and Li, 2013). While R&D is the actual amount of resources the firm sets aside each year for the purpose of creating and harvesting intellectual property, the stock of knowledge capital takes into account its depreciation rate and tabulates its net accumulation over time. Following prior literature (e.g., Cockburn and Griliches, 1988; Corrado, Hulten and Sichel, 2009; Eisfeldt and Papnikolaou, 2013, 2014; Corrado and Helton, 2014), I adopt the perpetual inventory model for the accumulation of knowledge capital:

$$KC_t = (1 - \delta)KC_{t-1} + R\&D_t \tag{1}$$

where KC_t is the stock of knowledge capital at the end of year t, $R\&D_t$ is research and development expenditure in year t, and δ is the depreciation rate of knowledge capital. While estimates for the depreciation rate vary, they tend to average around 15 to 20%. Following Eisfeldt and Papnikolaou (2013), Falato, Kadyrzhanova, and Sim (2013) and Peters and Taylor (2017), I set 15% as my depreciation rate of knowledge capital.[5] The perpetual inventory approach requires an estimate of the initial capital stock in year 0. If there are ten years or more of prior data on the firm's R&D, I assume the initial capital stock is zero; otherwise, it is estimated as:

$$KC_0 = \frac{R\&D_0}{g + \delta} \tag{2}$$

where g is the growth rate of the annual R&D expenditure (e.g., Hall, Mairesse and Mohnen, 2010). Given the initial capital stock, the stock of knowledge capital in subsequent years is updated via Eq. (1), using the lagged capital stock in the previous year, the current year's R&D expenditure and the assumed depreciation rate.

[5] For robustness, I also use 20% as the depreciation rate of knowledge capital. The results are not materially different.

For comparison and robustness, I also provide estimates for organization capital and intangible capital. The stock of organization capital is the capitalization of a firm's annual SG&A expenses, representing the firm's cumulative investment in human capital, brand, customer relationships and distribution systems. I estimate the stock of organization capital using the same perpetual inventory model, except that 30% of each year's SG&A expense is included in the organization capital calculation and depreciation rate is assumed to be 20% (e.g., Eisfeldt and Papanikolaou, 2014; Peters and Taylor, 2017). Given the estimate for both organization capital and knowledge capital for the firm in a given year, intangible capital is simply the sum of the two. As shown in Panel B of Table 1, knowledge capital and organization capital are on average 16.5% and 30.6% of the firm's total assets. The median figures are 3.5% and 23.0%, respectively. The variations are quite substantial, especially for knowledge capital, as no firm in the bottom quartile has any knowledge capital at all while all firms in the top quartile have knowledge capital that is at least 21.5% of total assets.

My second measure of a firm's investment of intellectual property is based on the output of that investment – the quantity and quality of patents the firm is granted each year. Although not all intellectual property is patentable, each firm's patent portfolio is a good proxy for its investment in intellectual property and technological innovation. This leads to my first two measures of output-based corporate innovation, the total number of patents granted to the firm each year (*Total Patents*) and the total number of citations received by all patents granted that year (*Total Citations*) over the following five years. While the former treats all patents equally, the latter adjusts for differences in the quality of the patents as proxied by the citations they receive.

Note that citation count for a given patent is not based on the raw count of all citations the patent has received. This is because citation count may vary widely depending on the year the patent is granted and the technology class the patent belongs to. Following common practice in the literature (e.g., Hall, Jaffe and Trajtenberg, 2001), citation count is adjusted for truncation lag based on citation lag-distribution using either the fixed effect approach or quasi-structural approach. My main empirical analysis is based on results from citation counts using the fixed effect approach, which scales the citation count for a given patent by the average citation count of all patents granted in the same year and in the same technology group. For robustness, I also use the alternative citation count calculated using the quasi-structural approach. For both alternative measures of citation count, I use NBER's categories of patents to estimate the patent count distribution.

Firms do not necessarily have patents granted every year; some firms may not have any patents at all. As shown in Panel B of Table 1, only about 38.3% (or 13,422/35,068) of all firm-years have a positive number of patents granted. In this subsample of firm-years, the average number of patents granted each year is roughly 55.8 (the median number is 10.0). The patent distribution is clearly highly skewed, with a small number of firms dominating patent grants. The distribution of citation counts is similar, with the average (median) number of citations in each firm-year being 65.8 (11.1).

Of course, not all patents are equally valuable to the firm. Breakthrough innovations are likely to create more value than incremental innovations do (Hall, Jaffe and Trajtenberg, 2005; Kogan et al., 2017). Incremental innovations are generally associated with the exploration of existing ideas and technology that are already familiar to the inventors. They require less resources in terms of the firm's R&D budget and inventors' time. These efforts are expected to produce more predictive outcomes and create incremental improvement to existing technology. In comparison, breakthrough innovations are associated with the exploration of unknown ideas or areas of technology that are beyond the inventors' expertise or unrelated to their past innovations. They generally require much more corporate resources and take more time to acquire. They are a high-risk, high-reward type of investment that may lead to disruptive innovations but there is also no guarantee it will succeed. Between these two types of innovations, it is clear that inventors of breakthrough innovations require more protection again poaching and are expected to receive more stock option grants.

To distinguish between breakthrough and incremental innovations, I rely on several commonly used measures in previous studies (Acemoglu, Akcigit and Ceilk, 2017; Balsmeier, Fleming and Manso, 2017; Gao, Hsu and Li, 2018; Lin, Liu and Manso, 2019). Patents are first divided into known and unknown types. A known (unknown) type of patent is a patent that is filed in technology classes that are previously known (unknown) to the firm. In other words, an unknown type is filed in a technology class that the firm has never filed before; a known type is exactly the opposite. While unknown types are more likely to be associated with breakthrough innovations, known types are more likely to be associated with incremental innovations. The total number of unknown patents, denoted *UnknownPatents*, granted to the firm in each year is my first proxy for the firm's breakthrough innovations. Similarly, the number of known patents, denoted *KnownPatents*, granted to the firm in each year is my first proxy for incremental innovations. As shown in Panel B of Table 1, nearly all patents are known patents, accounting for about 96% (53.505/55.763) of all patents granted each year. In fact, more than 75% of firm-years have no unknown patents granted at all. Breakthrough innovations are thus quite rare if I use known/unknown technology class to classify patents.

My second proxy for breakthrough (incremental) innovations is based on citation counts. Highly cited patents are more likely to be associated with breakthrough innovations than incremental innovations. For all patents granted each year, those that are among the top 10 percent of the citation count distribution are classified as breakthrough innovations. This classification leads to my second proxy for breakthrough innovations, *Top10%Citations*, which is the firm's total number of top 10 percent patents granted each year based on citation count. For incremental innovations, a parallel proxy is *Bottom90%Citations* which is the firm's total number of patents granted each year that are below the top 10 percent based on citation count. The sum of these two proxies is exactly equal to the total number of patents granted to the firm in that year (*Total Patents*). As shown in Panel C of Table 1, patents representing breakthrough innovations are still quite rare under this alternative classification in comparison with patents representing incremental innovations. More than 25 percent of firm-years have recorded no breakthrough innovations. Nevertheless, more than half of firm-years do have breakthrough innovations, allowing this alternative proxy to capture different types of breakthrough innovations than the ones based on known vs. unknown technology classes.

3 Empirical methodology

If firms indeed use RFOs as a retention tool to protect key employees from poaching by rival firms, they are expected to grant more RFOs when such threat is greater. Following this logic, I formulate several tests for the investigation of my main research questions about why some firms grant RFOs more extensively than other firms, whether or not firms target a subset of key employees for their RFO grants, and who are the target employees.

First, the threat of poaching is expected to be greater for firms that invest more in technological innovations. These firms allocate more resources, both financial and human resources, to research and development, and are more likely to have key personnel who are responsible for technological innovations. Rival firms may target and poach them in order to strengthen their own R&D programs and competitive position. While direct information about the presence or level of such talent at a given firm is not available, the stock of knowledge capital is a reasonable proxy for it. I thus test the retention motive using the following regression:

$$RFO_t = \alpha + \beta \times Knowledge\ Capital_{t-1} + Controls\ +\ \varepsilon_t \tag{3}$$

A positive relationship between RFOs and knowledge capital would lend support to the employee retention motive for the use of RFOs. The full list and definitions of all control variables are in the Appendix. These variables such as firm size, industry, leverage, past performance and stock return volatility are included to control for firm characteristics that may influence a firm's use of RFOs.

Secondly, the threat of poaching is expected to be greater for firms that have filed and received more patents, in comparison with their less innovative peer, especially if these patents are for breakthrough innovations. These firms not only have invested more in knowledge capital, but that investment has also been fruitful and led to the accumulation of invaluable intellectual property. Some of these firms may also have serial or "superstar" inventors who are responsible for breakthrough innovations and more likely to be the target of poaching by rival firms (Byun, Oh and Xia, 2020). Using patents as a proxy for inventors of intellectual property, I test the retention motive using the following regression:

$$RFO_t = \alpha + \beta \times Patents_t + Controls + \varepsilon_t \quad (4)$$

where $Patents_t$ is a measure of the patents granted to the firm in year t, including the total number of patents granted in year t (*Total Patents*), total citations received by these patents (*Total Citations*), the total number of patents granted that year that are considered to be breakthrough innovations (*Unknown Patents* or *Top10%Citations*), or the total number of patents granted that year that are considered to be incremental innovations (*Known Patents* or *Bottom90%Citations*).

Finally, I perform a quasi-natural experiment on the use of RFOs for the protection of intellectual property, taking advantage of state court's adoption and/or rejection of the IDD doctrine for preventing current or former employees from working for rival firms (Klasa et al., 2018). For firms located in states that have adopted the IDD, there is external protection against rival firms from poaching their key employees. Current and former employees are prohibited from working for a rival firm if these employees have intimate knowledge of trade secrets and would inevitably bring with them to their new employer, resulting in harm to their previous employer. The state court's adoption or rejection of the IDD is thus an exogenous shock to the ability for protecting their intellectual property for all firms in that state. For firms in a state that has adopted the IDD, the need to use RFOs as retention tool for keeping key talents from poaching by rival firm is much reduced relative to firms in other states that have not adopted or rejected the IDD. I thus expect firms in states that have adopted the IDD to use less RFOs than in states that have not adopted or rejected the IDD. This hypothesis is tested using the following regression:

$$RFO_t = \alpha + \beta_1 \times IDD_t + \beta_2 \times Intellectual\ Property_t + \beta_3 \times HIGH_{IP,\,t} + \beta_4 \times (HIGH_{IP,\,t} \cdot IDD_t) + Controls + \varepsilon_t \quad (5)$$

where IDD_t is an indicator variable that is 1 if the firm is in a state that the IDD is in effect in year t and 0 otherwise, *Intellectual Property* is a proxy for investment in intellectual property (*Knowledge Capital*, *Total Patents* or *Total Citations*), and $HIGH_{IP}$ is an indicator variable that is equal to 1 if the firm has above median level of *Intellectual Property* and 0 otherwise. This regression allows me to perform a difference-in-difference analysis of the use of RFOs between firms in states with and without the IDD protection.

4 Empirical findings

4.1 RFOs and knowledge capital

Corporate innovation is closely tied to a firm's investment in its R&D program. The stock of knowledge capital is a proxy for the cumulative investment in such program. The more investment a firm makes in knowledge capital, the more likely it has on its payroll key talents who are critical to corporate innovation. If RFOs are used for employee retention purposes, I expect their use to be greater for firms with a higher level of investment in knowledge capital. My first empirical test is thus focused on how the use of RFOs is related to the firm's investment in knowledge capital. The null hypothesis is that the use of RFOs is unrelated to investments in knowledge capital. Given the talent and other key personnel involved in a firm's R&D program, it would be difficult to argue for the employee retention motive if the null hypothesis is not rejected by the test results.

To empirically test this hypothesis, I run a regression of the total number of RFOs as a fraction of outstanding shares against Knowledge Capital and control variables, as described in Eq. (3). I also include Organization Capital in the regression to see if the use of RFOs has a broader purpose than just retaining key employees involved in corporate innovation. Unlike knowledge capital, organization capital is not directed at the research and development of technological or other innovations; instead, it is an investment in employee training, brand, customer relationships and distribution systems (Peters and Taylor, 2017). By including both Organization Capital and Knowledge Capital in the regression, I aim to differentiate alternative motives for granting RFOs. Are they used for attracting and retaining key employees involved in corporate innovation or for other corporate purposes? Results of these regressions are summarized in Table 2.

Table 2

As shown in column (2) of Table 2, the use of RFOs is indeed much greater for firms that have a higher level of investment in knowledge capital. The coefficient of Knowledge Capital is positive and statistically significant at the 1% level. In particular, a one-standard deviation increase in Knowledge Capital from its average level (16.5% of total assets) is expected to raise the use of RFOs by 24.0% from its mean (1.97% of shares outstanding). The impact is clearly economically substantial. It confirms a strong positive relationship between the use of RFOs and the firm's investment in knowledge capital. In comparison, I find no relationship at all between the use of RFOs and the firm's organization capital. The coefficient of Organization Capital is negligible in magnitude (very close to zero) and statistically insignificant. This is confirmation that the use of RFOs is positively associated with investments in knowledge capital but unrelated with investments in organization capital.

Of course, the positive association does not necessarily mean that firms use RFOs to retain key employees who are involved in their R&D program. There could be unknown factors that are behind the positive relationship. One way to find out is to run the same regression on stock options granted to the CEO and verify whether or not a similar relationship is present for CEO option grants. While vesting restrictions do provide a retention motive, stock options are granted to the CEO primarily for incentive alignment purposes. If a similar relationship also exists between CEO option grants and knowledge capital, then retaining key talents may not be the only reason for the use of RFOs. There might be common factors, which are not yet accounted for, that could be driving both relationships. As shown in column (4) of Table 2, the relationship between intangible capital and CEO option grants is clearly different from the corresponding relationship between intangible capital and RFOs. The most striking difference is that both Knowledge Capital and Organization Capital have influence on CEO option grants. Both coefficients are positive and statistically significant at the 5% level. The coefficient of Knowledge Capital is also much smaller in magnitude (only about 5.1% of the size of the corresponding coefficient in the RFO regression), suggesting a much weaker link with CEO option grants. These results indicate that firms may have a different motive for granting stock options to their CEOs than to rank-and-file employees. While RFOs are much more likely to be used for retention purposes, CEO option grants are more likely to be used for incentive alignment purposes.

4.2 RFOs and patents

While knowledge capital represents investment in the research and development of intellectual property, patents provide an alternative measure based on the output of that investment. At the same time, how much to invest in knowledge capital is likely to be part of the firm's overall corporate strategy and decided by its executive team. It is thus not surprising that the CEO's stock option grants are positively related to the level of knowledge capital (Table 2). On the other hand, the output of that investment is more likely to depend on employing the right team of talented personnel for carrying out the research and development activities. In this case, RFOs can be a useful tool for retaining these key talents who are crucial in creating intellectual property. I thus expect a strong relationship between the use of RFOs and the growth of the firm's patent portfolio. The same relationship is less likely between CEO stock option grants and patents because the CEO is evaluated on the firm's overall performance as opposed to the growth of the firm's patent portfolio. The firm's patent portfolio is thus a unique mechanism for isolating out the employee retention motive for the use of RFOs.

To verify if this is indeed the case, I first run a regression of a firm's RFOs against the total number of patents (Total Patents) awarded to the firm each year and citations these patents receive (Total Citations) as described in Eq. (4), including both concurrent and lagged measures of these variables. To minimize the impact of outliers, I apply logarithmic transformation, ln(1+x), for each patent/citation count variable x included in the regression. In addition, including concurrent independent variables is usually not a good idea due to endogeneity concerns. For patent variables, this is not necessarily the case because of the gap between the time a patent application is filed with the United States Patent and Trademark Office (USPTO) and the time it is granted by the USPTO. According to the USPTO, it takes roughly 23 months on average to get a patent approved. Even if the applicant pays an extra fee to expedite the process, it may still take as much as 9 months to have a decision on the patent application. This means that patents granted in a given year are typically filed with the USPTO in prior years. Including concurrent count of patents is thus less likely to create endogeneity problems.

The RFO regression results reported in Table 3 confirm a positive relationship between the use of RFOs and the firm's patents. The coefficient is positive and statistically significant for both Total Patents and Total Citations. The use of RFOs is thus strongly related to the total number of patents granted each year and the quality of those patents. I thus establish a linkage of a firm's use of RFOs with both of its investment in knowledge capital and the output of that investment, providing further support for the employee retention motive. In addition, I also separate patents into two non-overlapping subsets formed by those associated with breakthrough innovations (Unknown Patents or Top10%Citations) and those associated with incremental innovations (Known Patents or Bottom90%Citations). I then include them separately in the RFO regressions and report the results in Table 4. It is clear that the relationship between the use of RFOs and breakthrough innovations is stronger than the corresponding relationship between the use of RFOs and incremental innovations. For breakthrough innovations, the coefficient is positive and statistically significant for both UnknownPatents and Top10%Citations. It confirms a strong positive relationship between breakthrough innovations and the use of RFOs. In comparison, the impact of incremental innovations on the use of RFOs is much weaker, with the coefficient of Known Patents and Bottom90%Citations much smaller and statistically insignificant in the latter case. When both Top10%Citations and Bottom90%Citations are included in the regression (column 4), only the coefficient of Top10%Citations is large (and positive) and statistically significant at the 1% level; the coefficient of Bottom90%Citations is negative (and very small) and statistically insignificant. It suggests that firms target their RFOs for breakthrough innovations instead of incremental innovations. The results are similar if Unknown Patents and Known Patents are included in the regression (column 2), except that the coefficient of Known Patents is also statistically significant at the 1%. The economic significance of Known Patents is much smaller however as its coefficient is only about 12% the size of the corresponding coefficient of Unknown Patents. These findings are consistent with firms using RFOs to attract and retain their top talents who are more likely to be responsible for creating breakthrough innovations.

Tables 3

Tables 4

More importantly, there is no parallel relationship between CEO stock option grants and the firm's patent portfolio. In Table 5, I report the results of regressions of the CEO's stock option grants on the firm's patents, in parallel to the results of the RFO regressions in Table 3. None of the patent variables has any impact on the CEO's stock option grants, including Total Patents, Total Citations and their lags. All coefficients are close to zero and none of them is statistically significant. There is thus no evidence of any relationship at all between the CEO's stock option grants and the firm's patent portfolio. Un-tabulated results also show that a similar lack of any relationship between stock options granted to other top executives (i.e., other than the CEO) and the firm's patent portfolio. This is in direct contrast to the strong positive relationship between a firm's RFOs and its patent portfolio. These results are consistent with the idea that firms use RFOs to attract and retain employees involved in the research and development of intellectual property and protect them against poaching by rival firms.

Table 5

4.3 RFOs and the IDD: a quasi-natural experiment

Empirical results thus far are clearly consistent with the employee retention motive for using RFO grants. It is nevertheless premature to rule out alternative explanations such as the presence of unknown or unobserved variables that are driving the positive relationship between the use of RFOs and a firm's investment in intellectual property. In this section, I use an exogenous shock to external protection for a firm's trade secrets to re-examine this relationship and address endogeneity concerns. Specifically, the adoption and/or rejection of the IDD by U.S. state courts provide a quasi-natural experiment for testing the retention motive of RFO grants.

Similar to Klasa et al. (2018), I take advantage of the staggered adoption, and several cases of the subsequent rejection, of the IDD by U.S. state courts and perform difference-in-difference tests of the employee retention hypothesis. By the first year of my sample period in 1992, nine states (DE, FL, IL, MI, MN, NJ, NY, NC and PA) had adopted the IDD; another 12 states (AR, CT, GA, IN, IA, KS, MA, MO, OH, TX, UT and WA) adopted it during my sample period from 1992 to 2014 while three states (FL, MI and TX) rejected their previous adoption of the IDD (see Table 1 in Klasa et al., 2018). As such, there is a varying number of states that the IDD is in effect in any given year over my sample period, from a low of 9 states in 1992 to a high of 20 states in 2000. Such variations allow me to compare firms in states that have adopted the IDD with comparable firms in states that have not in the same year. This comparison is facilitated by the IDD dummy variable which is set equal to 1 if the firm is located in a state that the IDD is in effect in that year and 0 otherwise.

I begin my empirical analysis by first investigating if the adoption of the IDD has any impact on a firm's knowledge capital and patent portfolio. With or without the additional protection against poaching by rival firms provided by the IDD, intellectual property remains crucial for a firm's long-term success, its competitive position against rival firms in particular. I thus do not expect the adoption of the IDD to have any effect on a firm's investment in knowledge capital or the output of such investment. This is confirmed by the regression results in Table 6 where I summarize the results of regressing knowledge capital (column 2) and patent measures (columns 6 and 7) on the IDD dummy and control variables. The adoption of the IDD appears to have a negative impact on both the investment in knowledge capital and its output. However, the impact is quite small and does not appear to be economically significant as the coefficient of the IDD dummy variable is close to zero and statistically insignificant in all cases. Relatedly, I also find that the adoption of the IDD has no impact at all on organization capital (column 3), annual R&D expense (column 4) or annual SG&A expenditures (column 5). These results confirm that the IDD adoption is indeed an exogenous shock to the relationship between intellectual property and the use of RFOs because it has no impact at all on any of the variables related to intellectual property.

Table 6

A more relevant question is how the adoption or rejection of the IDD in state courts impact the use of RFOs. To answer this question, I utilize the IDD dummy to perform a difference-in-difference test of that relationship, together with $HIGH_{IP}$ dummy in order to differentiate between firms with high vs low levels of intellectual property, as described in Eq. (5). I use *Knowledge Capital*, *Total Patents* or *Total Citations* as proxy for intellectual property (*IP*). This allows me to examine both the impact of the IDD adoption on the use of RFOs and how the impact differ between firms with high vs. low levels of intellectual property. Results of these regressions are reported in Table 7.

Consistent with expectations, the adoption of the IDD indeed has a negative impact on the use of RFOs by firms in states where the IDD is in effect. In the regression reported in column (1) of Table 7, only the IDD dummy is included with the control variables. The coefficient of the IDD dummy variable is negative but statistically insignificant. Economically, though, the impact is not negligible. On average, the total number is RFOs granted by firms in my sample is about 1.97% of shares outstanding each year (Table 1). Using this average figure to interpret the coefficient of the IDD dummy variable, firms in states where the IDD is in effect use 21.5% (0.4238/1.972) less RFOs than firms in states where the IDD is not in effects. The impact of the IDD adoption is clearly economically substantial, even though it is not statistically significant.

Table 7

More importantly, the impact of the IDD adoption is drastically different between firms with a high level of investment in intellectual property and those with a low level of such investment. In the regressions reported in columns (2)-(4) of Table 7, I add the $HIGH_{IP}$ dummy and its interaction term with the *IDD* dummy where *Intellectual Property* is proxied by *Knowledge Capital*, *Total Patents* and *Total Citations*, respectively. In these regressions, the *IDD* variable captures the impact of the IDD adoption on the use of RFOs for low IP firms while the interaction term $HIGH_{IP} \times IDD$ captures the difference in the impact of the IDD adoption on the use of RFOs between high and low IP firms. It is clear that the impact is weak for low IP firms, both economically and statistically, but strong for high IP firms. Take the results reported in column (2), for example. Here, *Knowledge Capital* is used as proxy for investment in intellectual property. The coefficient of the IDD dummy is only –0.0347, suggesting that low IP firms in states where the IDD is in effect reduce their use of RFOs by only 1.8% (0.0347/1.972) than low IP firms in states where the IDD is not in effects. The impact of the IDD adoption is thus economically minimal and statistically insignificant. In comparison, the coefficient of the interaction term $HIGH_{KC}$×*IDD* is –0.5745 which is statistically significant at the 1% level, confirming the differential impact of the IDD adoption on the use of RFOs between high and low IP firms. To measure the impact of the IDD adoption on the use of RFOs for high IP firms, I need to combine of the coefficients of the *IDD* dummy and the interaction term $HIGH_{KC}$×*IDD*, which is equal to –(0.0347 + 0.5745) = –0.6092. It suggests that high IP firms in states where the IDD is in effect reduce their use of RFOs about 30.9% (0.6092/1.972) more than high IP firms in states where the IDD is not in effects. This is clearly a very large reduction in the use of the RFOs for high IP firms, in contrast to the minimal reduction for low IP firms. If I use patents as proxy for intellectual property, columns (3) and (4), the results are qualitatively similar, providing further confirmation of the differential impact. These findings suggest that not all firms use RFOs for employee retention purposes. They provide support for the argument that firms with a high level of investment in intellectual property do use RFOs for employee retention while firms with a low level of such investment are much less likely to do so.

Of course, the previous analysis hinges on the parallel trends assumption that both treatment and control firms have similar trends prior to the adoption of the IDD and the difference between them only emerges after the adoption. What if the difference is also present prior to the adoption of the IDD? In that case, reverse causality is a possible explanation for the results in Table 7. To rule out such possibility, I study the timing of change in the RFOs surrounding the IDD adoption. For firms in a state that has adopted the IDD in my sample period, I use indicator variables to capture the timing of the changes in RFOs surrounding the IDD adoption. Specifically, indicator variable IDD adoption$^{\Delta t}$ is 1 if the firm is located in a state that has adopted the IDD doctrine Δt years before or after the current year (t) and zero otherwise. For control firms in other states, all indicator variables are zero throughout the sample period. I then run regressions of RFOs on the indicator variables, using a three-year window both before and after the IDD adoption ($-3 \leq \Delta t \leq 3$), and control variables to capture the timing of changes. The results are summarized in Table 8 for the full sample and the subsample of firms with high Knowledge Capital (above the median). Results for the subsample firms with low Knowledge Capital (below the median) are similar and thus omitted for brevity.

Table 8

As shown in Table 8, the coefficients of the IDD indicator variables are mostly negative, with some exceptions (e.g., $\Delta t = -1$), suggesting that treatment firms tend to grant less RFOs both before and after the adoption of the IDD doctrine. However, these coefficients are typically small and never significant at any conventional level of statistical significance. The null hypothesis of parallel trends between treatment and control firms cannot be rejected. Reverse causality is unlikely the reason for the larger reduction of RFOs by firms with more investments in intellectual property after the IDD adoption.

In addition, I also run regressions of the CEO's stock option grants (*CEO Options*) on the IDD dummy and the interaction term $HIGH_{IP} \times IDD$ as well as a proxy for intellectual property (*Knowledge Capital*, *Total Patents* or *Total Citations*) and control variables, using a regression equation identical to Eq. (5) except that the variable *RFOs* is replaced with *CEO Options.* The regression results are summarized in Table 9. As the results in Table 9 indicate, both the IDD dummy variable and the interaction term $HIGH_{IP} \times IDD$ have little impact on the CEO's stock option grants. Both coefficients are very small and statistically insignificant. These results suggest that the adoption of the IDD by state courts have no impact at all on the CEO's stock option grants, for either high IP firms or low IP firms. Firms clearly deploy RFOs differently than they do with option grants for their CEOs.

Table 9

5 Robustness tests

5.1 Option expensing under FAS123R

The passage and implementation of the FAS123R has led to two exogenous shocks to the use of stock options in the compensation of top executives and rank-and-file employees. For one thing, it changes the way firms report their stock option grants to the public. Of the numerous changes, the one most relevant to the present study is that firms no longer report each top executive's option grant as a percentage of the firm's total number of options granted that year. It is no longer possible to calculate the total number of stock options each firm grants to their rank-and-file employees using the ExecuComp database (which is built from annual reports firms file with the SEC). Instead, I use another data source, Compustat, that does report the total number of stock options granted by the firm each year. This change may lead to inconsistencies in my estimate of the total number of RFOs before and after the implementation of FAS123R. This is however only a minor concern as I have verified that the potential inconsistencies are quite minimal (as discussed in Section 2.1).

More importantly, the implementation of FAS123R has led to a subsequent migration from stock options to restricted stock (and performance-vested equity pay in general) in the compensation of top executives and rank-and-file employees (Hayes, Lemmon and Qiu, 2012; Murphy, 2012; Edmans, Gabaix and Jenter, 2017). It would not be a surprise if the use of RFOs for employee retention purposes is impacted negatively by the implementation of FAS123R in 2006. To verify whether or not this is the case, I rerun the RFO regressions by including a FAS123R indicator variable which is equal to 1 if the year is 2006 or after and 0 otherwise and an interaction term with patent measures. UnknownPatents and KnownPatents are used as proxy for breakthrough and incremental innovations, respectively. The regression results are reported in Table 10. Results using Top10%Citations and Bottom90%Citations as proxies for breakthrough and incremental innovations are similar and thus omitted for brevity.

Table 10

It is quite clear that the adoption of FAS123R has a fairly large negative impact on the use of RFOs by U.S. firms. The coefficient of the FAS123R dummy variable varies between –1.765 to –1.915 across the four regressions reported in Table 10, suggesting that RFO grants as a percentage of shares outstanding declines by about 1.765 to 1.915 percentage points after the implementation of FAS123R. As RFO grants for each firm-year are on average 1.972% of shares outstanding, the decline in the use of RFOs is quite dramatic. It does not necessarily mean that firms have stopped providing equity incentives for employee retention purposes. It just means that RFOs play a reduced role in retaining employees after the implementation of FAS123R.

In addition, the implementation of FAS123R has also impacted the relationship between the use of RFOs and the firm's investment in technological innovation. Prior to the implementation of FAS123R in 2006, the use of RFOs has a strong positive relationship with technological innovation as proxied by patents granted each year. This is true for both breakthrough innovations (UnknownPatents) and incremental innovations (KnownPatents). This positive relationship is weakened considerably after the implementation of FAS123R. The coefficient of the interaction term between the FAS123R dummy and technological innovation (either UnknownPatents or KnownPatents) is negative and statistically significant at the 1% level. This is consistent with the notion that firms use more RFOs for employee retention purposes when the accounting cost (in the form of reduced reported earnings) is low. These same firms reduce the use of RFOs for employee retention purposes after the accounting cost becomes much higher and is now actually on par with other forms of equity pay after the implementation of FAS123R. This is consistent is with the widespread migration from stock options to restricted stock (or performance-vested equity) in the compensation of top executives and rank-and-file employees under FAS123R.

More importantly, the positive relationship between the use of RFOs and intellectual property seems to have diminished after the implementation of FAS123R. Take breakthrough innovations for example. The coefficient of Unknown Patents is 1.1788 in column (2) and statistically significant at the 1% level, confirming the positive relationship prior to the implementation of FAS123R. In comparison, the corresponding coefficient for the interaction term of the FAS123R dummy and Unknown Patents in the same regression is –1.1098 and statistically significant at the 1% level. Combining both coefficients, the net effect of Unknown Patents on the use of RFOs after the implementation of FAS123R is only 0.0690 (1.1788 – 1.1098). The positive relationship between the use of RFOs and breakthrough innovations is thus diminished after the implementation of FAS123R. The same outcome is obtained if I look at the relationship between the use of RFOs and incremental innovations reported in column (4). These results suggest that firms may have stopped using RFOs for the purpose of retaining key employees involved in the research and development of intellectual property after the implementation of FAS123R. They may have begun pursuing alternative strategies to retain these key employees when the accounting cost of RFOs is on par with that of other equity pay (e.g., restricted stock).

5.2 Neighborhood effect

An alternative explanation for the use of RFOs is the *neighborhood effect* identified by Kedia and Rajgopal (2009). They argue that neighboring firms share similar policies for granting stock options to rank-and-file employees because of local labor market conditions and social interactions among nearby firms. In a tight local labor market, stock options help retain employees as they vest over time. In addition, outside employment opportunities for rank-and-file employees are mostly located in nearby firms. This makes RFOs an even more appropriate retention tool because stock prices co-move more with stock prices of other firms located in the same neighborhood. The positive co-movement means that RFOs are more valuable precisely when employees' outside employment opportunities are more plentiful (Oyer, 2004; Oyer and Schaefer, 2005). This is clearly a different mechanism for employee retention than what I have identified here in the present chapter.

To distinguish between the two different mechanisms for using RFOs for employee retention purposes, I include the neighborhood effect in my RFO regressions. Specifically, I use the location of a firm's headquarters to identify its neighboring firms within a 60-mile radius, based on the locations of other firms' headquarters. I then calculate the average of RFOs as a fraction of shares outstanding for these neighboring firm, denoted *Local Avg RFOs*, and use it as a proxy for the neighborhood effect. This proxy is included in the RFO regression on a firm's investment in technological innovations. *UnknownPatents* and *KnownPatents* are used as proxy for breakthrough and incremental innovations, respectively. The regression results are reported in Table 11. Results using *Top10%Citations* and *Bottom90%Citations* as proxy for breakthrough and incremental innovations are similar and thus omitted for brevity.

Table 11

It is clear that the neighborhood effect on rank-and-file stock options is substantial. In all regressions reported in Table 11, the coefficient of *Local Avg RFOs* is positive and statistically significant at the 1% level. Its magnitude varies in a narrow range from 0.516 to 0.521, suggesting that about 52% of the variations in a firm's RFO grants are influenced by the variations of its neighbors' RFO grants. However, the strong, positive relationship between a firm's use of RFOs and its investment in technological innovation remains even after the neighborhood effect is accounted for. The coefficients for both *UnknownPatents* and *KnownPatents* are still positive and statistically significant. Their magnitude is somewhat reduced, in comparison with the corresponding regressions when the neighborhood proxy is not included (as reported in Table 4). Protection against the poaching of key personnel involved in the research and development of technological innovation remains a valid mechanism for the use of RFOs in employee retention.

5.3 Alternative methods for patent citation adjustment

Up to this point, my empirical analysis has utilized measures of technological innovation that are based on adjusted patent citation counts using the fixed-effect approach. I choose this approach because it is simple to implement and free of specification errors. Although this approach is reasonable and commonly used in the literature, I want to make sure that my results are robust to this choice. I thus consider an alternative estimation method and implement the quasi-structural approach that relies on the fitting of a non-linear model of the citation lag-distribution to patent citation data. Details of this alternative approach are in Hall, Jaffe and Trajtenberg (2001). Using this alternative approach, I recalculate my measures of technological innovation such as *Total Citations* and *Top10%Citations*. I then rerun the RFO regressions using the alternative measures to investigate the robustness of the relationship between the use of RFOs and the firm's investment in technological innovation. The results are summarized in Table 12.

Table 12

Results in Table 12 confirm that the positive relationship between the use of RFOs and the firm's investment in technological innovation is robust to the choice of methods for citation count adjustment. Take *Total Citations* for example, which is a measure of the firm's overall technological innovation based on the quality of the patents granted to the firm. If I use the quasi-structural approach to calculate this innovation measure, as is done for the RFO regression reported in column (3) of Table 12, its coefficient is +0.1014 and statistically significant at the 1% level. In comparison to the same RFO regression reported in column (3) of Table 3 where citation count is adjusted using the fixed-effect approach, its coefficient is +0.1694 and statistically significant at the 1% level. The magnitude of the positive effect in the new regression is smaller than estimated previously but remains statistically and economically significant. Results of the other three RFO regressions reported in Table 12 provide further support for the positive relationship between the use of RFOs and the firm's investment in technological innovation. The employee retention hypothesis is thus robust to the choice of citation count adjustment methods.

6 Conclusions

Why do firms grant stock options to rank-and-file employees even though these employees individually have little ability to influence the stock price? Prior research generally agrees that attracting and retaining employees is the most likely motive for granting these options and provides alternative explanations such as the tight local labor market hypothesis (e.g., Almazan, De Motta and Titman, 2007; Kedia and Rajgopal, 2009; Lee, Thornton and Xu, 2019) and the wage indexation hypothesis (Oyer, 2004; Oyer and Schaefer, 2005).

In this chapter, I identify the precise mechanism that firms utilize RFO grants and the subset of key employees they target for these grants. In particular, I show that firms grant more stock options to rank-and-file employees if they invest more in intellectual property. This is true irrespective of how intellectual property is measured, either by the cumulative resources devoted to the research and development of such property (e.g., the stock of *knowledge capital*) or by the actual acquisitions of such property (i.e., patents). In comparison, there is no relationship at all between RFO grants and *organization capital*, suggesting that the use of RFOs is unrelated to investment in employee training, brand, customer relationships and distribution systems. It further highlights the important role intellectual property such as patents play in the decision to grant stock options to rank-and-file employees.

In addition, not all intellectual property impacts RFO grants in the same manner. In particular, breakthrough innovations play a more important role in the use of RFOs for retention purposes than incremental innovations do. The use of RFOs is more responsive to patents that are more revolutionary than evolutionary, such as those in the technology class that the firm has never had any patents before or those that are ranked within the top 10% of the adjusted citation count distribution among all patents granted that year. In comparison, the relationship is much weaker between the use of RFOs and patents that represent incremental innovations. It provides additional support that the use of RFOs is motivated by the recruiting and protection of key personnel involved in the research and development of intellectual property, especially those responsible for breakthrough innovations.

I also take advantage of an exogenous shock to the protection of trade secrets against rival firms and show that firms do reduce their use of RFOs after the adoption of the IDD by the state courts where the firm is located, relative to control firms whose headquarters are in states where the IDD is not in effect. However, the effect is only detected in firms with above median level of investment in intellectual property but not in firms with below median level of such investment. As the availability of external legal protection against poaching by rival firms reduces the need for firms to use RFOs for retention purposes, it appears that only firms with a high level of investment in intellectual property grant RFOs for employee retention purposes; there is little evidence that firms with a low level of investment in intellectual property use them that way.

I contribute to the literature by identifying the type of firms that use RFOs for retention purposes and the subset of employees targeted by these option grants. Although any employee turnover is potentially costly to the firm, it is even more costly when it is the turnover of key personnel involved in the research and development of intellectual property, especially those responsible for breakthrough innovations. I fill the gap in the literature by recognizing the importance of intellectual property and how the use of RFOs is linked to the development and protection of such property. The distinct roles played by knowledge vs. organization capital and breakthrough vs. incremental innovations provide further confirmation of this relationship.

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8 Tables

Table 1

Descriptive statistics.

This table reports summary statistics of stock options granted to the CEO and rank-and-file employees, measures of corporate innovation such as knowledge capital, patent and citation counts, and control variables for firm characteristics in the period 1992-2014. Stock options (*RFOs* and *CEO Options*) are calculated as a fraction of the firm's shares outstanding. RFOs are estimated by subtracting stock options granted to top executives from the total number of options granted to all employees. Knowledge capital is a measure of investments in corporate innovations, estimated using the perpetual inventory model by capitalizing R&D expenditures at a 15% depreciation rate. Productivity of knowledge capital is measured by patents, via Total Patents which is the number of patents granted to the firm in a given year and Total Citations which is the total number of citations received by these patents. Citation count is adjusted for truncation lag using the fixed-effect approach. Patents are classified as either breakthrough or incremental innovations. Breakthrough (incremental) innovations are proxied by either *Unknown* (*Known*) *Patents* or *Top10%Citations* (*Bottom90%Citations*). *Unknown* (*Known*) *Patents* is the number of patents granted each year that are in technology classes previously unknown (known) to the firm. *Top10%Citations* (*Bottom90%Citations*) is the number of patents granted each year that fall into the top 10% (bottom 90%) of the citation distribution among all patents granted in the same year. Details of control variables for firm characteristics are in the Appendix. All continuous variables are winsorized at 1% and 99%.

	Mean	Median	Q1	Q3	SD	OBS
Panel A: Stock option grants						
RFOs ($000)	14,627	3,736	4.445	11,047	39,652	35,068
RFOs (%)	1.972	0.755	0.047	2.127	3.646	35,068
CEO Options ($000)	1,342	259	0	1,406	2,757	35,068
CEO Options (%)	0.243	0.042	0	0.236	0.531	35,068
Panel B: Measures of corporate innovations						
Intangible Capital	0.465	0.346	0.151	0.617	0.468	28,651
Organizational Capital	0.306	0.230	0.110	0.409	0.287	31,671
Knowledge Capital	0.165	0.035	0.000	0.215	0.293	29,012
Total Patents	55.763	10.000	3.000	36.000	143.692	13,422
Known Patents	53.505	9.000	3.000	35.000	137.804	13,377
Unknown Patents	0.203	0.000	0.000	0.000	0.630	13,377
Total Citations	65.812	11.144	2.859	43.740	166.963	13,377
Top 10% Citations	7.921	1.000	0.000	5.000	20.286	13,377
Bottom 90% Citations	55.909	8.000	2.000	30.000	214.082	13,377
Panel C: Control variables						
Cash flow shortfall	-0.171	-0.168	-0.248	-0.099	0.139	32,786
Interest burden	0.194	0.113	0.044	0.250	0.228	29,980
R&D/Sales	0.130	0.029	0.005	0.111	0.437	20,433
Book-to-market	0.624	0.612	0.416	0.813	0.275	33,428
Long-term debt dummy	0.830	1.000	1.000	1.000	0.376	34,858
Low marginal tax dummy	0.047	0.000	0.000	0.000	0.212	17,232
High marginal tax dummy	0.414	0.000	0.000	1.000	0.493	17,232
Log (Sales)	6.972	6.927	5.885	8.062	1.686	34,970
Log (Employees)	1.545	1.585	0.395	2.708	1.716	34,415
Operating loss dummy	0.115	0.000	0.000	0.000	0.319	34,969
Past stock performance	0.213	0.118	-0.139	0.410	0.620	32,592
Stock return volatility	0.121	0.104	0.074	0.148	0.067	30,448

Table 2

Knowledge capital and stock option grants.

This table reports the regression results of RFOs and CEO Options on knowledge capital, organization capital and intangible. Knowledge capital is a measure of investments in corporate innovations, estimated using the perpetual inventory model by capitalizing R&D expenditures at a 15% depreciation rate. Organization capital is estimated using the perpetual inventory model by capitalizing SG&A expenses using a 30% inclusion rate and 20% depreciation rate. Intangible capital is sum of knowledge capital and organization capital. All three forms of intangible capital are calculated as a percentage of total assets. Details of control variables for firm characteristics are in the Appendix. All continuous variables are winsorized at 1% and 99%. Numbers in parenthesis are *t*-statistics and ***, ** and * denote 1%, 5% and 10% statistical significance, respectively. Clustered standard errors are calculated at the firm level.

	Dependent variable:			
	Rank & File Option (%)		CEO Option (%)	
	(1)	(2)	(3)	(4)
Intangible Capital	0.6816***		0.0735***	
	(4.2075)		(3.3173)	
Knowledge Capital		1.6169***		0.0824**
		(5.8762)		(2.3552)
Organizational Capital		0.0065		0.0914**
		(0.0247)		(2.2385)
Cash flow shortfall	-3.1413***	-3.2627***	-0.1688**	-0.1765***
	(-6.2455)	(-6.4981)	(-2.4560)	(-2.6179)
Interest burden	0.1511	0.0709	0.0828*	0.0802*
	(0.5963)	(0.2770)	(1.8834)	(1.8296)
R&D/Sales	0.4186*	0.1301	-0.0295	-0.0244
	(1.7829)	(0.5403)	(-1.1557)	(-0.8837)
Book-to-market	-0.5665**	-0.4192*	0.0768**	0.0807**
	(-2.4138)	(-1.7869)	(2.2182)	(2.3821)
Long-term debt dummy	-0.2101	-0.1978	0.0441**	0.0456**
	(-1.2463)	(-1.1833)	(2.0767)	(2.1321)
Low marginal tax dummy	0.0533	0.0253	-0.0502	-0.0506
	(0.1950)	(0.0937)	(-1.3741)	(-1.3823)
High marginal tax dummy	-0.0522	-0.0482	-0.0081	-0.0078
	(-0.4446)	(-0.4133)	(-0.4466)	(-0.4306)
Log (Sales)	0.5162***	0.4852***	-0.0045	-0.0040
	(5.7357)	(5.5080)	(-0.4148)	(-0.3713)
Log (Employees)	-0.5399***	-0.5125***	-0.0399***	-0.0399***
	(-6.1656)	(-5.9872)	(-3.6308)	(-3.6283)

Past stock performance	-0.0261	-0.0079	-0.0144	-0.0134
	(-0.4008)	(-0.1222)	(-1.3536)	(-1.2832)
Stock return volatility	5.2662***	5.1885***	0.0203	0.0160
	(5.5967)	(5.5335)	(0.1406)	(0.1113)
Operating loss dummy	0.0877	0.0152	-0.0599***	-0.0629***
	(0.5610)	(0.0990)	(-3.0153)	(-3.2335)
Observations	26,358	26,358	26,358	26,358
Industry Fixed Effect	YES	YES	YES	YES
Year Fixed Effect	YES	YES	YES	YES
Adjusted R^2	0.1040	0.1061	0.0373	0.0377

Table 3

Rank-and-file option grants and technological innovation

This table reports the regression results of rank-and-file option grants (RFOs) on technological innovations. RFOs are all options granted to the firm's employees other than the top executives, as a fraction of shares outstanding. Two proxies are used for technological innovation, *Total Patents*, which is the number of patents granted to the firm in a given year, and *Total Citations*, which is the total number of citations received by these patents. Citation count is adjusted for truncation lag using the fixed-effect approach. Patents are classified as either breakthrough or incremental innovations. Log transformation, ln(1+*x*), is applied to all patent variables in order to reduce the impact of outliers. Details of control variables for firm characteristics are in the Appendix. All continuous variables are winsorized at 1% and 99%. Numbers in parenthesis are *t*-statistics and ***, ** and * denote 1%, 5% and 10% statistical significance, respectively. Clustered standard errors are calculated at the firm level.

	Dependent variable:			
	Rank and File Option (%)			
	(1)	(2)	(3)	(4)
Total Patents	0.1124***	0.4269***		
	(3.2717)	(5.5959)		
Total Patents$_{-1}$		-0.0759		
		(-1.1509)		
Total Patents$_{-2}$		-0.0486		
		(-0.6993)		
Total Patents$_{-3}$		-0.2409***		
		(-2.7058)		
Total Citations			0.1694***	0.3849***
			(4.9971)	(5.6480)
Total Citations$_{-1}$				-0.0347
				(-0.6523)
Total Citations$_{-2}$				-0.0884
				(-1.5082)
Total Citations$_{-3}$				-0.1362**
				(-2.0018)
Cash flow shortfall	-2.7099***	-2.5597***	-2.7053***	-2.5996***
	(-6.0790)	(-5.8981)	(-6.0820)	(-5.9260)
Interest burden	0.2393	0.2532	0.2396	0.2503
	(0.8755)	(0.9273)	(0.8778)	(0.9184)
R&D/Sales	0.3949	0.3507	0.3861	0.3560
	(1.6075)	(1.4436)	(1.5800)	(1.4528)
Book-to-market	-0.9297***	-0.9243***	-0.8628***	-0.8740***

	(-4.6395)	(-4.6405)	(-4.3767)	(-4.4339)
Long-term debt dummy	-0.1704	-0.1719	-0.1564	-0.1596
	(-1.1526)	(-1.1669)	(-1.0605)	(-1.0835)
Low marginal tax dummy	0.1004	0.1289	0.0752	0.1001
	(0.2463)	(0.3164)	(0.1856)	(0.2477)
High marginal tax dummy	-0.2240*	-0.2242*	-0.2155*	-0.2202*
	(-1.8629)	(-1.8684)	(-1.7960)	(-1.8357)
Log (Sales)	0.1955**	0.1976**	0.1656*	0.1714*
	(2.1618)	(2.1879)	(1.8434)	(1.9046)
Log (Employees)	-0.3654***	-0.3524***	-0.3620***	-0.3530***
	(-4.3269)	(-4.1898)	(-4.2980)	(-4.2069)
Past stock performance	-0.0711	-0.0719	-0.0629	-0.0679
	(-1.3336)	(-1.3484)	(-1.1796)	(-1.2760)
Stock return volatility	5.2537***	5.0601***	5.1697***	5.0151***
	(6.1893)	(5.9564)	(6.0876)	(5.9338)
Operating loss dummy	0.4501***	0.4446***	0.4263***	0.4308***
	(3.0480)	(3.0204)	(2.9112)	(2.9447)
Observations	31,990	31,990	31,990	31,990
Industry Fixed Effect	YES	YES	YES	YES
Year Fixed Effect	YES	YES	YES	YES
Adjusted R^2	0.0969	0.0980	0.0980	0.0988

Table 4

Rank-and-file option grants and breakthrough innovations

This table reports the regression results of rank-and-file option grants (RFOs) on breakthrough and incremental innovations. Breakthrough (incremental) innovations are proxied by either *Unknown* (*Known*) *Patents* or *Top10%Citations* (*Bottom90%Citations*). *Unknown* (*Known*) *Patents* is the number of patents granted each year that are in technology classes previously unknown (known) to the firm. *Top10%Citations* (*Bottom90%Citations*) is the number of patents granted each year that fall into the top 10% (bottom 90%) of the citation distribution among all patents granted in the same year. Log transformation, ln(1+*x*), is applied to all patent variables in order to reduce the impact of outliers. Details of control variables for firm characteristics are in the Appendix. All continuous variables are winsorized at 1% and 99%. Numbers in parenthesis are *t*-statistics and ***, ** and * denote 1%, 5% and 10% statistical significance, respectively. Clustered standard errors are calculated at the firm level.

	Dependent variable:			
	Rank and File Option (%)			
	(1)	(2)	(3)	(4)
Unknown Patents	0.8087***	0.7998***		
	(3.4377)	(3.4047)		
Known Patents		0.0993***		
		(2.8386)		
Top10%Patents			0.2984***	0.4033***
			(4.9220)	(4.1694)
Bottom90%Patents				-0.0855
				(-1.4997)
Cash flow shortfall	-2.6243***	-2.6656***	-2.6738***	-2.6422***
	(-5.9064)	(-5.9952)	(-6.0353)	(-5.9679)
Interest burden	0.2491	0.2432	0.2484	0.2546
	(0.9111)	(0.8912)	(0.9088)	(0.9316)
R&D/Sales	0.3760	0.3821	0.3737	0.3630
	(1.5247)	(1.5531)	(1.5282)	(1.4810)
Book-to-market	-0.9968***	-0.9255***	-0.8784***	-0.8863***
	(-4.9268)	(-4.6282)	(-4.4316)	(-4.4640)
Long-term debt dummy	-0.1874	-0.1747	-0.1533	-0.1518
	(-1.2705)	(-1.1825)	(-1.0339)	(-1.0225)
Low marginal tax dummy	0.1427	0.1117	0.0898	0.0968
	(0.3473)	(0.2741)	(0.2204)	(0.2379)
High marginal tax dummy	-0.2357*	-0.2263*	-0.2237*	-0.2264*
	(-1.9556)	(-1.8825)	(-1.8622)	(-1.8852)
Log (Sales)	0.2367***	0.1957**	0.1711*	0.1805**

	(2.6196)	(2.1676)	(1.8887)	(1.9928)
Log (Employees)	-0.3557***	-0.3589***	-0.3615***	-0.3580***
	(-4.2042)	(-4.2505)	(-4.2942)	(-4.2439)
Past stock performance	-0.0850	-0.0718	-0.0699	-0.0752
	(-1.6047)	(-1.3509)	(-1.3127)	(-1.4117)
Stock return volatility	5.1670***	5.1593***	5.1250***	5.0723***
	(6.1059)	(6.0958)	(6.0297)	(5.9956)
Operating loss dummy	0.4873***	0.4450***	0.4395***	0.4556***
	(3.3180)	(3.0178)	(3.0021)	(3.0817)
Observations	31,990	31,990	31,990	31,990
Industry Fixed Effect	YES	YES	YES	YES
Year Fixed Effect	YES	YES	YES	YES
Hypothesis	Unknown Patents = Known Patents		Top10%Citations = Bottom90%Citations	
t-test	2.9365***		3.3543***	
Adjusted R^2	0.0970	0.0975	0.0978	0.0980

Table 5

CEO option grants and technological innovation

This table reports the regression results of CEO option grants (CEO Options) on technological innovations. CEO Options is all stock options granted to the CEO in a year, as a fraction of shares outstanding. Two proxies are used for technological innovation, *Total Patents*, which is the number of patents granted to the firm in a given year, and *Total Citations*, which is the total number of citations received by these patents. Citation count is adjusted for truncation lag using the fixed-effect approach. Patents are classified as either breakthrough or incremental innovations. Log transformation, ln(1+*x*), is applied to all patent variables in order to reduce the impact of outliers. Details of control variables for firm characteristics are in the Appendix. All continuous variables are winsorized at 1% and 99%. Numbers in parenthesis are *t*-statistics and ***, ** and * denote 1%, 5% and 10% statistical significance, respectively. Clustered standard errors are calculated at the firm level.

	Dependent variable:			
	CEO Options (%)			
	(1)	(2)	(3)	(4)
Total Patents	0.0030	-0.0060		
	(0.6832)	(-0.5240)		
Total Patents$_{-1}$		0.0075		
		(0.6646)		
Total Patents$_{-2}$		-0.0003		
		(-0.0310)		
Total Patents$_{-3}$		0.0029		
		(0.2546)		
Total Citations			0.0061	0.0031
			(1.3604)	(0.3276)
Total Citations$_{-1}$				0.0032
				(0.3650)
Total Citations$_{-2}$				-0.0021
				(-0.2611)
Total Citations$_{-3}$				0.0024
				(0.2443)
Cash flow shortfall	-0.1216*	-0.1243**	-0.1219*	-0.1230**
	(-1.9296)	(-1.9903)	(-1.9355)	(-1.9745)
Interest burden	0.0737*	0.0734*	0.0737*	0.0736*
	(1.7856)	(1.7805)	(1.7854)	(1.7843)
R&D/Sales	-0.0200	-0.0192	-0.0203	-0.0200
	(-0.8802)	(-0.8441)	(-0.8933)	(-0.8775)
Book-to-market	0.0367	0.0367	0.0399	0.0401

	(1.1371)	(1.1363)	(1.2410)	(1.2453)
Long-term debt dummy	0.0292	0.0292	0.0299	0.0299
	(1.3196)	(1.3203)	(1.3459)	(1.3462)
Low marginal tax dummy	-0.0194	-0.0200	-0.0207	-0.0208
	(-0.5342)	(-0.5470)	(-0.5685)	(-0.5727)
High marginal tax dummy	-0.0391**	-0.0390**	-0.0387**	-0.0387**
	(-2.0723)	(-2.0690)	(-2.0524)	(-2.0491)
Log (Sales)	-0.0176	-0.0177	-0.0192	-0.0193
	(-1.4386)	(-1.4457)	(-1.5589)	(-1.5661)
Log (Employees)	-0.0354***	-0.0356***	-0.0353***	-0.0353***
	(-3.0888)	(-3.0889)	(-3.0812)	(-3.0766)
Past stock performance	-0.0179*	-0.0179*	-0.0175*	-0.0174*
	(-1.7819)	(-1.7802)	(-1.7380)	(-1.7371)
Stock return volatility	0.1741	0.1772	0.1709	0.1723
	(1.2036)	(1.2230)	(1.1817)	(1.1917)
Operating loss dummy	-0.0468**	-0.0467**	-0.0481**	-0.0482**
	(-2.3323)	(-2.3314)	(-2.4081)	(-2.4076)
Observations	31,990	31,990	31,990	31,990
Industry Fixed Effect	YES	YES	YES	YES
Year Fixed Effect	YES	YES	YES	YES
Adjusted R^2	0.0328	0.0328	0.0329	0.0328

Table 6

The impact of the IDD adoption on corporate innovations

This table reports the results of difference-in-difference regressions that assess the impact of the IDD adoption on a firm's investment in corporate innovations. An indicator variable, IDD which is 1 if the firm is located in a state the IDD is in effect and 0 otherwise, is used to facilitate the regression analysis. Knowledge capital and patents are used as proxies for input and out of that investment. Knowledge capital is estimated using the perpetual inventory model by capitalizing R&D expenditures at a 15% depreciation rate. Organization capital is estimated using the perpetual inventory model by capitalizing SG&A expenses using a 30% inclusion rate and 20% depreciation rate. Intangible capital is sum of knowledge capital and organization capital. All three forms of intangible capital are calculated as a percentage of total assets. *Total Patents* and *Total Citations* are the number of patents granted to the firm in a given year and citation count of these patents, respectively. Citation count is adjusted for truncation lag using the fixed-effect approach. Patents are classified as either breakthrough or incremental innovations. Log transformation, ln(1+*x*), is applied to all patent variables in order to reduce the impact of outliers. Details of control variables for firm characteristics are in the Appendix. All continuous variables are winsorized at 1% and 99%. Numbers in parenthesis are *t*-statistics and ***, ** and * denote 1%, 5% and 10% statistical significance, respectively. Clustered standard errors are calculated at the firm level.

	Dependent variable:						
	Intang. Capital	Knowl. Capital	Organ. Capital	R&D/ Sales	SG&A/ Sales	Total Patents	Total Citations
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
IDD	-0.027	-0.030	0.000	-0.010	0.000	-0.109	-0.146
	(-0.888)	(-1.273)	(0.002)	(-0.887)	(0.025)	(-0.878)	(-1.030)
Cash flow shortfall	0.827***	0.466***	0.393***	0.059**	0.169***	0.682**	0.482
	(7.959)	(7.909)	(6.376)	(1.973)	(2.598)	(2.214)	(1.520)
Interest burden	0.164**	0.114***	0.061	0.018	0.007	-0.083	-0.116
	(2.415)	(3.236)	(1.548)	(0.700)	(0.193)	(-0.447)	(-0.614)
Book-to-market	-0.307***	-0.218***	-0.105***	-0.105***	-0.218***	-0.495***	-0.756***
	(-9.359)	(-10.009)	(-4.994)	(-6.121)	(-8.262)	(-3.956)	(-5.438)
Long-term debt dummy	-0.133***	-0.074***	-0.056***	-0.011***	-0.030***	-0.236**	-0.279***
	(-6.281)	(-7.844)	(-3.785)	(-2.681)	(-3.553)	(-2.324)	(-2.654)
Low marginal tax dummy	0.163***	0.102***	0.053***	0.004	0.016	0.274***	0.330***
	(4.524)	(3.031)	(3.501)	(0.352)	(0.692)	(3.322)	(3.828)
High marginal tax dummy	-0.039***	-0.019*	-0.019***	-0.009***	-0.021***	-0.052	-0.088
	(-2.869)	(-1.777)	(-2.869)	(-3.220)	(-3.707)	(-0.883)	(-1.362)
Log (Sales)	-0.020*	0.019**	-0.042***	-0.005	-0.056***	0.709***	0.757***
	(-1.712)	(2.455)	(-4.786)	(-0.938)	(-5.446)	(13.813)	(12.626)

Log (Employees)	-0.016	-0.034***	0.020**	-0.004	0.027***	-0.018	-0.059
	(-1.312)	(-4.647)	(2.494)	(-0.845)	(2.884)	(-0.349)	(-0.959)
Past stock performance	-0.088***	-0.054***	-0.037***	-0.012***	-0.032***	-0.148***	-0.159***
	(-8.571)	(-6.339)	(-9.011)	(-6.612)	(-9.633)	(-6.941)	(-6.867)
Stock return volatility	0.347**	0.207**	0.100	0.123***	0.150***	0.172	0.705
	(2.128)	(2.511)	(1.206)	(4.545)	(2.663)	(0.380)	(1.398)
Operating loss dummy	0.327***	0.204***	0.123***	0.095***	0.188***	0.554***	0.551***
	(18.133)	(17.979)	(10.345)	(8.996)	(11.891)	(9.907)	(7.632)
Observations	17,535	17,535	17,535	17,535	17,535	17,535	17,535
Industry Fixed Effect	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effect	YES	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.378	0.451	0.311	0.336	0.456	0.531	0.481

Table 7

The impact of the IDD adoption on the use of rank-and-file options

This table reports the results of difference-in-difference regressions that assess the impact of the IDD adoption on the use of rank-and-file options. An indicator variable, IDD which is 1 if the firm is located in a state the IDD is in effect and 0 otherwise, is used to facilitate the regression analysis. Knowledge Capital is estimated using the perpetual inventory model by capitalizing R&D expenditures at a 15% depreciation rate. Knowledge Capital is then scaled by total assets for cross sectional comparison. *Total Patents* and *Total Citations* are the number of patents granted to the firm in a given year and citation count of these patents, respectively. Citation count is adjusted for truncation lag using the fixed-effect approach. Patents are classified as either breakthrough or incremental innovations. Log transformation, ln(1+*x*), is applied to both patent variables in order to reduce the impact of outliers. $HIGH_{KC}$, $HIGH_{TP}$ and $HIGH_{TC}$ are indicator variables that take the value of 1 if the firm's Knowledge Capital, Total Patents and Total Citations are in the top half of all firms, respectively, and zero otherwise. Details of control variables for firm characteristics are in the Appendix. All continuous variables are winsorized at 1% and 99%. Numbers in parenthesis are *t*-statistics and ***, ** and * denote 1%, 5% and 10% statistical significance, respectively. Clustered standard errors are calculated at the firm level.

	Dependent variable: Rank & File Options (%)			
	(1)	(2)	(3)	(4)
IDD	-0.4238	-0.0347	-0.1170	-0.1250
	(-1.3646)	(-0.2207)	(-0.4934)	(-0.5329)
Knowledge Capital (KC)		1.3423***		
		(6.4295)		
$HIGH_{KC}$		0.8672***		
		(3.3891)		
IDD × $HIGH_{KC}$		-0.5745***		
		(-2.6136)		
Total Patents (TP)			0.0638	
			(1.0650)	
$HIGH_{TP}$			0.5005**	
			(2.1133)	
IDD × $HIGH_{TP}$			-0.6479***	
			(-3.5829)	
Total Citations (TC)				0.1703***
				(5.6689)
$HIGH_{TC}$				0.2178
				(1.4974)
IDD × $HIGH_{TC}$				-0.6401***
				(-3.5473)
Cash flow shortfall	-2.4954***	-3.2138***	-2.5252***	-2.5159***

	(-2.8897)	(-3.3341)	(-3.1015)	(-3.0870)
Interest burden	0.2935	0.1657	0.2804	0.2821
	(1.0022)	(0.6214)	(0.9965)	(1.0015)
Book-to-market	-0.8853***	-0.3560**	-0.7722***	-0.7181***
	(-4.6068)	(-2.4213)	(-4.2919)	(-4.2279)
Long-term debt dummy	-0.2895**	-0.1920	-0.2599*	-0.2414*
	(-2.1829)	(-1.6230)	(-1.9048)	(-1.8019)
Low marginal tax dummy	0.1628	0.0198	0.1245	0.1033
	(0.6717)	(0.0913)	(0.5189)	(0.4405)
High marginal tax dummy	-0.0914	-0.0353	-0.0656	-0.0617
	(-0.8239)	(-0.2847)	(-0.5542)	(-0.5100)
Log (Sales)	0.4907***	0.4738**	0.4424**	0.4053**
	(2.6081)	(2.5137)	(2.3058)	(2.3729)
Log (Employees)	-0.5462***	-0.5088***	-0.5405***	-0.5413***
	(-2.7972)	(-2.7004)	(-2.8994)	(-2.9102)
Past stock performance	-0.0979	-0.0150	-0.0803	-0.0746
	(-1.4889)	(-0.2758)	(-1.2608)	(-1.2123)
Stock return volatility	5.6425***	5.0220***	5.5917***	5.4897***
	(4.9970)	(4.4708)	(4.8539)	(4.7903)
Operating loss dummy	0.3197***	0.0140	0.2644**	0.2424**
	(2.8333)	(0.1091)	(2.3946)	(2.1362)
Observations	25,826	25,826	25,826	25,826
Industry Fixed Effect	YES	YES	YES	YES
Year Fixed Effect	YES	YES	YES	YES
Adjusted R^2	0.1026	0.1095	0.1043	0.1052

Table 8

The timing of changes in RFOs surrounding the IDD adoption

This table reports the results of OLS regressions of RFOs on dummy variables for the timing of the IDD adoption, covering three years before and after the recognition by state courts. "High Knowledge Capital" is the subsample of firms with Knowledge Capital above its median of all firms. IDD adoption^t is an indicator variable that takes the value of 1 if the firm is in a state that recognizes the IDD *t* years before or after the current year and zero otherwise, where $-3 \leq t \leq +3$. Details of control variables for firm characteristics are in the Appendix. All continuous variables are winsorized at 1% and 99%. Numbers in parenthesis are *t*-statistics and ***, ** and * denote 1%, 5% and 10% statistical significance, respectively. Clustered standard errors are calculated at the firm level.

	Dependent variable: Rank & File Options (%)			
	Full sample		High Knowledge Capital	
	(1)	(2)	(3)	(4)
IDD adoption^{-3}	-0.7715	-0.6645	-1.0264	-0.7538
	(-0.9207)	(-0.8676)	(-0.7874)	(-0.6452)
IDD adoption^{-2}	-0.6508	-0.5393	-0.9914	-0.7970
	(-0.8311)	(-0.7353)	(-0.8689)	(-0.7720)
IDD adoption^{-1}	0.0134	0.0349	-0.2048	-0.1444
	(0.0131)	(0.0368)	(-0.1514)	(-0.1190)
IDD adoption^{0}	-0.2400	-0.1508	-0.8772	-0.7833
	(-0.3404)	(-0.2423)	(-0.9292)	(-0.9556)
IDD adoption^{+1}	-0.0461	0.0572	-0.1848	-0.0302
	(-0.0732)	(0.1064)	(-0.2250)	(-0.0442)
IDD adoption^{+2}	-0.5925	-0.4930	-0.9715	-0.8004
	(-1.0515)	(-1.0411)	(-1.2540)	(-1.3006)
IDD adoption^{+3}	-0.0720	0.0115	-0.0783	0.0558
	(-0.1135)	(0.0198)	(-0.0728)	(0.0549)
Cash flow shortfall		-2.5322***		-3.5545***
		(-2.8925)		(-4.3543)
Interest burden		0.2726		0.4701
		(0.9586)		(1.1752)
Book-to-market		-0.8919***		-0.7965***
		(-4.1711)		(-3.8728)
Long-term debt dummy		-0.2913**		-0.3180**
		(-2.0623)		(-2.2673)
Low marginal tax dummy		0.1935		0.4832*
		(0.7799)		(1.6874)
High marginal tax dummy		-0.0820		0.0037

		(-0.7620)		(0.0259)
Ln (Sales)		0.4997**		0.8576**
		(2.5282)		(2.4571)
Ln (Employees)		-0.5635***		-1.0181***
		(-2.6526)		(-2.6976)
Past stock performance		-0.0961		-0.1126
		(-1.4437)		(-1.1626)
Stock return volatility		5.7845***		5.3802***
		(4.7902)		(5.1119)
Operating loss dummy		0.3431***		0.4721***
		(3.2249)		(3.1305)
Observations	25,826	25,826	15,730	15,730
Industry Fixed Effect	YES	YES	YES	YES
Year Fixed Effect	YES	YES	YES	YES
Adjusted R^2	0.0829	0.1010	0.0943	0.1182

Table 9

The impact of the IDD adoption on CEO option grants

This table reports the results of difference-in-difference regressions that assess the impact of the IDD adoption on CEO option grants. Knowledge Capital is estimated using the perpetual inventory model by capitalizing R&D expenditures at a 15% depreciation rate. Knowledge Capital is then scaled by total assets for cross sectional comparison. *Total Patents* and *Total Citations* are the number of patents granted to the firm in a given year and citation count of these patents, respectively. Citation count is adjusted for truncation lag using the fixed-effect approach. Patents are classified as either breakthrough or incremental innovations. Log transformation, ln(1+*x*), is applied to both patent variables in order to reduce the impact of outliers. $HIGH_{KC}$, $HIGH_{TP}$ and $HIGH_{TC}$ are indicator variables that take the value of 1 if the firm's Knowledge Capital, Total Patents and Total Citations are in the top half of all firms, respectively, and zero otherwise. Details of control variables for firm characteristics are in the Appendix. All continuous variables are winsorized at 1% and 99%. Numbers in parenthesis are *t*-statistics and ***, ** and * denote 1%, 5% and 10% statistical significance, respectively. Clustered standard errors are calculated at the firm level.

	Dependent variable: CEO Options (%)			
	(1)	(2)	(3)	(4)
IDD	0.0065	0.0017	0.0194	0.0200
	(0.3366)	(0.0797)	(1.2897)	(1.3826)
Knowledge Capital (KC)		0.0856**		
		(2.5415)		
$HIGH_{KC}$		0.0502**		
		(2.1654)		
IDD × $HIGH_{KC}$		0.0112		
		(0.3437)		
Total Patents (TP)			-0.0109**	
			(-2.0135)	
$HIGH_{TP}$			0.0641***	
			(2.5914)	
IDD × $HIGH_{TP}$			-0.0273	
			(-0.9137)	
Total Citations (TC)				-0.0026
				(-0.5080)
$HIGH_{TC}$				0.0473**
				(1.9700)
IDD × $HIGH_{TC}$				-0.0292
				(-0.9415)
Cash flow shortfall	-0.1309*	-0.1779**	-0.1310*	-0.1330*
	(-1.6966)	(-2.3636)	(-1.6701)	(-1.6988)

Interest burden	0.0901*	0.0838*	0.0899*	0.0894*
	(1.8019)	(1.7177)	(1.7977)	(1.7874)
Book-to-market	0.0564	0.0925***	0.0600*	0.0622*
	(1.6448)	(2.7560)	(1.6924)	(1.7490)
Long-term debt dummy	0.0355	0.0401*	0.0354	0.0363
	(1.4798)	(1.7060)	(1.4980)	(1.5396)
Low marginal tax dummy	-0.0384	-0.0465	-0.0389	-0.0403
	(-1.2147)	(-1.4646)	(-1.2350)	(-1.3111)
High marginal tax dummy	-0.0123	-0.0085	-0.0110	-0.0109
	(-0.6289)	(-0.4471)	(-0.5758)	(-0.5725)
Log (Sales)	-0.0063	-0.0075	-0.0048	-0.0076
	(-0.3674)	(-0.4302)	(-0.2744)	(-0.4813)
Log (Employees)	-0.0416***	-0.0392***	-0.0406***	-0.0411***
	(-2.7726)	(-2.6545)	(-2.7399)	(-2.7768)
Past stock performance	-0.0205*	-0.0152	-0.0201*	-0.0196*
	(-1.8635)	(-1.4541)	(-1.8029)	(-1.8003)
Stock return volatility	0.0651	0.0205	0.0637	0.0624
	(0.4943)	(0.1521)	(0.4811)	(0.4741)
Operating loss dummy	-0.0420*	-0.0619***	-0.0420*	-0.0443*
	(-1.9014)	(-2.9447)	(-1.8593)	(-1.8947)
Observations	25,826	25,826	25,826	25,826
Industry Fixed Effect	YES	YES	YES	YES
Year Fixed Effect	YES	YES	YES	YES
Adjusted R^2	0.0359	0.0372	0.0361	0.0360

Table 10

The impact of the FAS123R on rank-and-file option grants

This table reports the results of regressions that assess the impact of the implementation of the FAS123R on the use of rank-and-file option grants. An indicator variable, FAS123R which is 1 if the year is 2006 or after and 0 otherwise, is used to facilitate the regression analysis. *RFOs* is the total number of options granted to the firm's employees other than the top executives, as a fraction of shares outstanding. Breakthrough and incremental innovations are proxied by *Unknown Patents* and *Known Patents*, respectively. *Unknown* (*Known*) *Patents* is the number of patents granted each year that are in technology classes previously unknown (known) to the firm. Log transformation, ln(1+*x*), is applied to all patent variables in order to reduce the impact of outliers. Details of control variables for firm characteristics are in the Appendix. All continuous variables are winsorized at 1% and 99%. Numbers in parenthesis are *t*-statistics and ***, ** and * denote 1%, 5% and 10% statistical significance, respectively. Clustered standard errors are calculated at the firm level.

	Dependent variable:			
	Rank and File Option (%)			
	(1)	(2)	(3)	(4)
FAS123R	-1.9151***	-1.7976***	-1.9137***	-1.7650***
	(-18.0070)	(-16.7218)	(-18.0209)	(-14.7362)
Unknown Patents	0.9058***	1.1788***		
	(3.8426)	(3.6010)		
Unknown Patents$_{-1}$		0.3005		
		(1.2432)		
Unknown Patents$_{-2}$		0.2257		
		(0.8770)		
Unknown Patents$_{-3}$		0.9386***		
		(3.3424)		
Unknown Patents×FAS123R		-1.1098***		
		(-3.0949)		
Unknown Patents$_{-1}$×FAS123R		-0.3296		
		(-1.2472)		
Unknown Patents$_{-2}$×FAS123R		-0.2331		
		(-0.8420)		
Unknown Patents$_{-3}$×FAS123R		-0.9098***		
		(-3.0492)		
Known Patents			0.1035***	0.6449***
			(2.9500)	(5.8568)
Known Patents$_{-1}$				0.1365
				(1.3009)
Known Patents$_{-2}$				-0.0626

				(-0.6005)
Known Patents$_{-3}$				-0.6352***
				(-4.2839)
Known Patents×FAS123R				-0.6978***
				(-5.7332)
Known Patents$_{-1}$×FAS123R				-0.1696
				(-1.5064)
Known Patents$_{-2}$×FAS123R				0.1066
				(0.9906)
Known Patents$_{-3}$×FAS123R				0.6940***
				(4.3260)
Cash flow shortfall	-2.6773***	-2.6405***	-2.7661***	-2.5795***
	(-5.9736)	(-5.8817)	(-6.1459)	(-5.9343)
Interest burden	0.3102	0.3116	0.3004	0.3202
	(1.1606)	(1.1633)	(1.1245)	(1.2008)
R&D/Sales	0.3525	0.3443	0.3743	0.3282
	(1.4298)	(1.3952)	(1.5214)	(1.3457)
Book-to-market	-1.1105***	-1.0830***	-1.0566***	-1.0357***
	(-5.5471)	(-5.4218)	(-5.3149)	(-5.2539)
Long-term debt dummy	-0.0881	-0.0882	-0.0706	-0.0798
	(-0.5933)	(-0.5960)	(-0.4741)	(-0.5415)
Low marginal tax dummy	0.0923	0.0885	0.0491	0.0774
	(0.2241)	(0.2146)	(0.1203)	(0.1910)
High marginal tax dummy	0.2986***	0.2963***	0.3135***	0.2966***
	(2.7443)	(2.7227)	(2.8893)	(2.7382)
Log (Sales)	0.1306	0.1257	0.0937	0.0935
	(1.5450)	(1.4913)	(1.1044)	(1.1038)
Log (Employees)	-0.2848***	-0.2782***	-0.2955***	-0.2855***
	(-3.5153)	(-3.4398)	(-3.6502)	(-3.5436)
Past stock performance	-0.0996**	-0.0962**	-0.0878*	-0.0845*
	(-2.0411)	(-1.9797)	(-1.7884)	(-1.7268)
Stock return volatility	4.8752***	4.6242***	4.9477***	4.3955***
	(6.9328)	(6.6165)	(7.0149)	(6.1801)
Operating loss dummy	0.4930***	0.4783***	0.4636***	0.4347***
	(3.3333)	(3.2401)	(3.1179)	(2.9327)
Observations	31,990	31,990	31,990	31,990
Industry Fixed Effect	YES	YES	YES	YES
Year Fixed Effect	NO	NO	NO	NO
Adjusted R^2	0.0867	0.0879	0.0862	0.0898

Table 11

The neighborhood effect

This table reports the results of regressions that assess how other firms in the neighborhood impact a firm's use of rank-and-file option grants. *Local Avg RFOs* is the average RFOs, as a fraction of shares outstanding, across all other firms within the 60-mile radius of the firm's headquarters. For each firm, *RFOs* is the total number of options granted to the firm's employees other than the top executives, as a fraction of shares outstanding. Breakthrough and incremental innovations are proxied by *Unknown Patents* and *Known Patents*, respectively. *Unknown* (*Known*) *Patents* is the number of patents granted each year that are in technology classes previously unknown (known) to the firm. Log transformation, ln(1+*x*), is applied to all patent variables in order to reduce the impact of outliers. Details of control variables for firm characteristics are in the Appendix. All continuous variables are winsorized at 1% and 99%. Numbers in parenthesis are *t*-statistics and ***, ** and * denote 1%, 5% and 10% statistical significance, respectively. Clustered standard errors are calculated at the firm level.

	Dependent variable:			
	Rank and File Option (%)			
	(1)	(2)	(3)	(4)
Local Avg RFOs	0.5213***	0.5184***	0.5208***	0.5163***
	(7.8176)	(7.7613)	(7.8235)	(7.8017)
Unknown Patents	0.6722***	0.6358***		
	(2.8517)	(2.7878)		
Unknown Patents$_{-1}$		0.0672		
		(0.4031)		
Unknown Patents$_{-2}$		0.0450		
		(0.2426)		
Unknown Patents$_{-3}$		0.5684***		
		(2.9131)		
Known Patents			0.0605*	0.2552***
			(1.7734)	(3.9867)
Known Patents$_{-1}$				0.0563
				(0.8869)
Known Patents$_{-2}$				0.0050
				(0.0784)
Known Patents$_{-3}$				-0.2975***
				(-3.3923)
Cash flow shortfall	-2.2972***	-2.2814***	-2.3577***	-2.2272***
	(-5.5007)	(-5.4389)	(-5.6261)	(-5.4256)
Interest burden	0.3250	0.3206	0.3177	0.3264
	(1.2094)	(1.1893)	(1.1828)	(1.2159)

R&D/Sales	0.2008	0.2019	0.2166	0.1846
	(0.8425)	(0.8475)	(0.9090)	(0.7810)
Book-to-market	-0.8196***	-0.8011***	-0.7885***	-0.7784***
	(-4.1081)	(-4.0276)	(-3.9682)	(-3.9434)
Long-term debt dummy	-0.1220	-0.1238	-0.1119	-0.1150
	(-0.8606)	(-0.8741)	(-0.7866)	(-0.8107)
Low marginal tax dummy	0.0732	0.0648	0.0468	0.0625
	(0.1833)	(0.1622)	(0.1180)	(0.1580)
High marginal tax dummy	-0.2350**	-0.2316**	-0.2276*	-0.2238*
	(-1.9971)	(-1.9687)	(-1.9369)	(-1.9088)
Log (Sales)	0.1824**	0.1797**	0.1623*	0.1635*
	(2.0949)	(2.0671)	(1.8476)	(1.8633)
Log (Employees)	-0.2882***	-0.2842***	-0.2958***	-0.2849***
	(-3.5066)	(-3.4609)	(-3.6028)	(-3.4783)
Past stock performance	-0.0892*	-0.0857*	-0.0820	-0.0813
	(-1.7176)	(-1.6521)	(-1.5706)	(-1.5552)
Stock return volatility	3.9345***	3.8562***	4.0180***	3.8346***
	(4.7073)	(4.6258)	(4.7968)	(4.5669)
Operating loss dummy	0.3257**	0.3196**	0.3101**	0.3036**
	(2.2745)	(2.2351)	(2.1496)	(2.1090)
Observations	31,990	31,990	31,990	31,990
Industry Fixed Effect	YES	YES	YES	YES
Year Fixed Effect	YES	YES	YES	YES
Adjusted R^2	0.1178	0.1181	0.1174	0.1183

Table 12

Robustness to alternative adjustments for patent count truncation

This table reports the results of regressions that assess the robustness of alternative adjustments for patent count truncation. *RFOs* is the total number of options granted to the firm's employees other than the top executives, as a fraction of shares outstanding. *Total Citations* is the total number of citations received by all patents granted in a given year. *Top10%Patents* is a proxy for breakthrough innovation, defined as the number of patents granted each year that are ranked among the top 10% of the patent count distribution for all patents granted in the same year. Instead of using the fixed-effect approach, patent count is adjusted using the quasi-structural approach, by fitting a non-linear model of the citation lag-distribution to patent citation data. Log transformation, ln(1+*x*), is applied to all patent variables in order to reduce the impact of outliers. Details of control variables for firm characteristics are in the Appendix. All continuous variables are winsorized at 1% and 99%. Numbers in parenthesis are *t*-statistics and ***, ** and * denote 1%, 5% and 10% statistical significance, respectively. Clustered standard errors are calculated at the firm level.

	Dependent variable:			
	Rank and File Option (%)			
	(1)	(2)	(3)	(4)
Top10%Patents	0.4017***	0.5629***		
	(5.7592)	(5.4264)		
Top10%Patents$_{-1}$		0.1192		
		(1.4411)		
Top10%Patents$_{-2}$		-0.0577		
		(-0.7180)		
Top10%Patents$_{-3}$		-0.2905***		
		(-2.9032)		
Total Citations			0.1014***	0.2078***
			(4.9688)	(5.8598)
Total Citations$_{-1}$				-0.0245
				(-0.9202)
Total Citations$_{-2}$				-0.0447
				(-1.6045)
Total Citations$_{-3}$				-0.0636*
				(-1.9310)
Cash flow shortfall	-2.6413***	-2.5910***	-2.7167***	-2.6159***
	(-5.9962)	(-5.9404)	(-6.0966)	(-5.9404)
Interest burden	0.2443	0.2432	0.2360	0.2445
	(0.8960)	(0.8917)	(0.8654)	(0.8981)
R&D/Sales	0.3479	0.3392	0.3830	0.3528

	(1.4312)	(1.3950)	(1.5682)	(1.4450)
Book-to-market	-0.8183***	-0.8280***	-0.8449***	-0.8648***
	(-4.1615)	(-4.1886)	(-4.2928)	(-4.3917)
Long-term debt dummy	-0.1415	-0.1458	-0.1592	-0.1639
	(-0.9562)	(-0.9859)	(-1.0823)	(-1.1145)
Low marginal tax dummy	0.0628	0.0694	0.0651	0.0936
	(0.1545)	(0.1714)	(0.1606)	(0.2312)
High marginal tax dummy	-0.2201*	-0.2202*	-0.2104*	-0.2222*
	(-1.8369)	(-1.8391)	(-1.7569)	(-1.8513)
Log (Sales)	0.1467	0.1525*	0.1698*	0.1781**
	(1.6446)	(1.6991)	(1.9100)	(1.9996)
Log (Employees)	-0.3549***	-0.3510***	-0.3578***	-0.3507***
	(-4.2321)	(-4.1972)	(-4.2529)	(-4.1770)
Past stock performance	-0.0611	-0.0650	-0.0588	-0.0653
	(-1.1450)	(-1.2188)	(-1.0992)	(-1.2245)
Stock return volatility	5.0320***	4.9717***	5.1445***	5.0135***
	(5.9262)	(5.8569)	(6.0668)	(5.9293)
Operating loss dummy	0.4133***	0.4183***	0.4191***	0.4276***
	(2.8259)	(2.8621)	(2.8671)	(2.9248)
Observations	31,990	31,990	31,990	31,990
Industry Fixed Effect	YES	YES	YES	YES
Year Fixed Effect	YES	YES	YES	YES
Adjusted R^2	0.0991	0.0995	0.0983	0.0991

9 Appendix

9.1 List of variables and definitions

Name	Definition
RFOs	Number of options granted to all employees other than the top executives, as a percentage of shares outstanding.
CEO Options	Number of options granted to the CEO, as a percentage of shares outstanding.
Knowledge Capital	Stock of capitalized R&D expenditures using the perpetual inventory model with a 15% depreciation rate.
Organization Capital	Stock of capitalized SG&A expenses using the perpetual inventory model with a 30% inclusion rate and 20% depreciation rate.
Intangible Capital	Knowledge Capital + Organization Capital
Total Patents	Total number of patents granted to the firm each year.
Total Citations	Total number of citations received by all patents granted in a given year, adjusted for patent count truncations.
Known Patents	Number of patents granted to the firm in a given year that are in technology classes the firm has already been granted patents before.
Unknown Patents	Number of patents granted to the firm in a given year that are in technology classes the firm has never been granted any patents before.
Top10%Citations	Number of patents granted to the firms in a given year that are in the top 10% of the patent citation distribution of all patents granted that year.
Bottom90%Citations	Number of patents granted to the firms in a given year that are in the bottom 90% of the patent citation distribution of all patents granted that year.
IDD	Dummy variable for the IDD which is 1 if the firm is located in a state that the IDD is in effect that year and 0 otherwise.
FAS123R	Dummy variable for the implementation of FAS123R which is 1 if the year is 2006 or after and 0 otherwise.
Local Avg RFOs	The average number of RFOs, as a fraction of shares outstanding, across all other firms within a 60-mile radius of the firm's headquarters.
Cash flow shortfall	The three-year average of [(common dividends + preferred dividends + cash flow from investing - cash flow from operations)/total assets].
Interest burden	The three-average average of interest expense scaled by operating income before depreciation.
R&D/Sales	The three-year average of research and development expense scaled by sales.
Book-to-market	The three-year average ratio of book value of assets over the sum of book value of liabilities and market value of equity.

Long-term debt dummy	An indicator variable for long-term debt, which is equal to 1 if the firm has long-term debt outstanding and 0 otherwise.
Low marginal tax dummy	An indicator variable that is equal to 1 if the firm has negative taxable income and net operating loss carryforwards every year in the previous three years.
High marginal tax dummy	An indicator variable that is equal to 1 if the firm has positive taxable income and no net operating loss carryforwards every year in the previous three years.
Sales	Total sales each year.
Employees	Number of employees.
Past stock performance	The buy-and-hold stock return over the past 12 months.
Stock return volatility	Standard deviation of monthly stock returns in the past year.
Operating loss dummy	A dummy variable that is equal to one if the firm reports negative operating earnings in the year and 0 otherwise.

Chapter II

II Do rank-and-file stock option grants help with employee retention – Evidence from inventor retention.

Aman Khan

1 Introduction

The use of stock options as a form of managerial equity incentive has usually been attributed to aligning the interests of top executives with those of the shareholders. This is supported by the agency theory of firm for optimal risk sharing (Holmstrom,1979; Jensen and Murphy, 1990). Incentive alignment on the other hand is not a good explanation for the widespread use of stock option grants to rank-and-file employees (RFOs) due to dead-weight costs and free-rider problem (Bergman and Jenter, 2007).

Yet, firms still grant RFOs to their employees. The most cited motive is employee retention (Oyer, 2004; Oyer and Schaefer, 2005). Due to the delay between RFO grant and vesting, employees will forfeit the options if they leave the firm early. At the same time the positive correlation between the value of stock options and industry performance makes it very costly for the employee to leave when their outside opportunities are higher, thus creating a form of delayed compensation.

However, if employee retention is the motive, then why is there such widespread discrepancy between use of RFOs among firms, with some firms issuing a lot of RFOs and others hardly making any use of such options. A plausible explanation is that firms target only a subset of employees for retention, namely those involved in research and development. In chapter I, I provided evidence to suggest that firms that have a higher stock of knowledge capital and produce more intellectual property in the form of breakthrough innovation, are the ones that make heavy use of RFOs.

If the target of RFOs is the retention of inventors involved in R&D, then a natural question to ask is how well does it work? How effective are RFO grants in retaining inventors? Earlier studies (Aldatmaz et al., 2018) have focused on all employees working at the firm and find that option grants are effective at reducing employee turnover following a grant, but the effect is temporary. The reduction in employee turnover is reversed in the third year which is around the average vesting period for such stock option grants (Crimmel and Schildkraut, 2001; Oyer and Schaefer, 2005). Such a result is perhaps not surprising because firms may target the use of RFOs for retaining key personnels instead of all rank-and-file employees.

In this chapter, I focus on the retention of one set of key employees, inventors. Departure of an inventor to a new firm serves as a mechanism to transfer the inventor's old firm-specific knowledge to the new firm (Khanna R, 2022). The turnover of inventors results in the loss of tacit knowledge, which is likely to make the use of their patents as a foundation for future inventions challenging. As such the loss of an inventor has both direct and indirect costs and their loss over a short time span of three years compared to the 20 years that a patent can provide protection would make the use of RFOs highly ineffective as a retention tool.

I exploit a large panel of inventor level data and match these inventors to the firms that employ them. I then measure the inventor turnover at the firm level as the fraction of inventors leaving the firm relative to the average level of inventor employment at the firm. Immediately following an RFO grant I find there to be a reduction in inventor turnover at these firms. The drop in inventor turnover is strong both in terms of statistical significance (1% significance) as well as economic significance (a drop of 36% in average inventor turnover). These results seem to confirm the delayed compensation view of RFOs and their use as a means for ensuring that inventor turnover can be kept in check in the short-term.

As mentioned earlier, option grants play a key role in controlling employee turnover in the short-term with a reversal in turnover 3 years after the option grant. At the same time, inventor turnover has both direct and indirect costs and can make a part of the portfolio of patents held by the firm worthless when the inventor leaves. As such I look at how good RFOs are at keeping inventors at the firm beyond the initial grant and look at the lasting impact of RFOs in the 5 years after the RFO grants and their effect on inventor turnover. I find that RFOs are effective in reducing inventor turnover up to 3 years after their grant. This result is in stark contrast to earlier findings which find that the effect of RFO on overall employee turnover is temporary because they find that turnover rate increases in the two years after the RFO grant but the increase is fully reversed in the third year, with virtually no change at all in turnover in the 3-year period after the RFO grant.. I find that the turnover rate decreases all the way up to 3 years. This agrees with the key insight that firms make use of RFOs for retaining their key personnel, namely inventors, and as such the effectiveness of RFOs should be measured through their effectiveness at retaining inventors. Also, I find little evidence of a reversal in RFOs' effectiveness in retaining inventors over the 5 year period after the grant, further highlighting the fact that RFOs are an important tool for ensuring inventors stay with their incumbent firm for the long term. I also repeat these results with a shorter 3-year lag window as a robustness check and find similar results. Of course, these results only show a strong correlation between RFO grant and inventor turnover. Studies have shown causality between employee turnover and option grants (Aldatmaz et al., 2018). I provide further proof for causality through the following tests.

A natural question to ask is that if firms target inventor retention through the granting of RFOs, then do inventors value these options when it comes to their decision to stay or leave the firm. This also doubles up as a robustness check to ensure that my previous results are not due unobserved or missing variable bias as it is hard to argue that RFOs are effective at inventor retention if the inventors themselves don't value the options. My unique setting of inventor level data helps me answer this question. I exploit the change in employment of inventors in my sample and measure the probability to leave the incumbent firm. My results show that the probability to leave the firms goes down when the incumbent firm offers more RFOs. This reduction is about 1.66% for a $14,307 (1 standard deviation) increase in RFO per employee. The actual effect is likely even stronger since RFO per employee is only a proxy for the RFOs received by the individual inventor and there is no reason to believe every employee at a firm receives RFOs or the same number of RFOs. Unsurprisingly, I also find that the probability to leave goes up when the new firm offers more RFOs. These results are statistically significant at the 1% level of significance and show that inventors do value RFOs received by them through their decision to stay or leave.

I further test the causal link by the unique changes to the rules for option expensing brought on by the implementation of FAS123R. FAS123R was an accounting change that was implemented in 2006 and made it very costly for firms to issue stock options by having them - expense the granted options in the same year as their grant. There was a reduction in RFO grants following the adoption of FAS123R (Hayes, Lemmon and Qiu, 2012). Thus, FAS123R gives me a unique external shock which leads to a drop in the use of RFOs and at the same time should have no impact directly on inventor turnover. I find that in the period following the adoption of FAS123R there was a significant increase in inventor turnover to the tune of almost 170% compared to the average inventor turnover over the entire sample. Further, my results show that firms that offer more RFOs in the post FAS123R period see a significant decline in inventor turnover of around 37%. This is even more impressive when we consider that the overall inventor turnover levels are higher in the post FAS123R period. These results help me establish the causal link between RFOs and inventor turnover.

My contribution to the existing literature is as follows. I have looked deeper into use of RFOs for inventor retention and find that unlike the case for the average employee, RFOs are highly effective in retaining inventors through a reduction in inventor turnover. I find no evidence that the effect is temporary which suggests that the use of RFOs by firms is a successful strategy for keeping their inventors and preventing their poaching by rival firms. Further, I also show that the individual inventors value these RFO grants through a reduction in their probability to leave the firm when such RFO grants are made. Finally, I show that RFOs are important tools for reducing inventor turnover in periods of high turnover as seen for the period after adoption of FAS123R.

The rest of the chapter proceeds as follows. Section 2 describes the sample of firms and inventors and provides descriptive statistics of their characteristics. In Section 3, I describe my empirical methodology and details of the empirical tests. In Section 4, I empirically investigate the relationship between the use of RFOs and their effectiveness as a retention tool. Section 5 provides robustness checks. The final section concludes.

2 Data and descriptive statistics

2.1 Rank-and-file stock option grants

My sample includes all firms covered by the Standard and Poors' ExecuComp database from 1992 to 2010. ExecuComp provides data on the dollar value of stock option grants to executives at the firm. Although more recent data are available, I choose 2010 as my last year in the sample because inventor tracking data from the Harvard Business School (HBS) U.S. Patent Inventor Database (Li et al. 2014) is only available till 2010. After excluding firms in the utility and financial industries (with two-digit SIC codes of 49 and 60-69 inclusive), I have a total of 35,432 firm-year observations. As firms do not report the number of RFOs granted each year, I infer this number from the total amount of options granted to all employees and the total amount of options granted to the top five executives (e.g., Oyer and Schaefer, 2005; Kedia and Rajgopal, 2009; Call, Kedia and Rajgopal, 2016).

In extracting data for each year's RFOs, adjustments are made due to a change in the way firms report stock option grants during my sample period. During the period between 1992 and 2006, firms report stock option grants under the so-called "old" reporting format (e.g., Cole, Daniel and Naveen, 2006). Under this format, firms not only report the amount of stock options granted to each top executive for the fiscal year but also these options as a fraction of all options granted to all employees by the firm (variable PCTTOTOPT). This allows for an accurate tabulation of stock options granted to the CEO, other top executives, and all options granted by the firm. Subtracting the options granted to top executives from all options granted by the firm, I have a proxy for the number of RFOs granted in each fiscal year.

During the period between 2007 and 2010, firms report stock option grants under the "new" reporting format mandated by the Financial Accounting Standard Board under FAS123R. Although more details of stock option grants are disclosed, firms no longer report each executive's option grants as a fraction of all options granted by the firm. In this case, I rely on Compustat to find the total amount of options granted (variable OPTGR) by the firm in each fiscal year (Kedia and Rajgopal, 2009; Call, Kedia and Rajgopal, 2016). From this total option grant figure, I calculate RFOs as before by subtracting out stock options granted to top executives. To make sure this approach is valid, I recalculate RFOs during the period between 1992 and 2006 using Compustat's OPTGR and compare with the amount calculated using ExecuComp's PCTTOTOPT. The two values of RFOs match nearly perfectly, supporting the use of Compustat's OPTGR for total amount of options granted by the firm in a fiscal year. I also use Compustat for all control variables used in this chapter.

Table 1

From Panel A of Table 1, I see that firms in my sample grant on average around $14.88 million RFOs with the median number being around $3.33 million. This skewed distribution highlights the fact that not all firms make similar use of RFOs, with firms involved in more corporate innovation being the ones making substantial use of RFOs as I showed in chapter 1.

2.2 Tracking inventors patenting career

Before I can assess how RFOs impact inventor retention at firms, I need to identify the firms they are working at. Given the public nature of the patenting process, I have access to inventor information of every granted patent and use inventor patenting activity to create an inventor-level dataset tracking their employment and patenting activity following a process similar to Li and Wang (2020).

I begin with the Harvard Business School (HBS) U.S. Patent Inventor Dataset (Li et al. 2014), henceforth the HBS database, which provides me with disambiguated inventor information on granted patents from 1975-2010. I use the patent assignee data constructed from the USPTO by researchers at Duke University as described by Arora, Belenzon and Sheer (2021), henceforth the Duke database. The Duke database contains information on granted patents and their assignees over 1980-2015, and their extension to the commonly used NBER patent data (Hall, Jaffe and Trajtenberg, 2001; Bessen, 2009) improves the matching of assignees (name of company filing the patent) and Compustat firms by addressing name changes and ownership changes. The database is also used to calculate various patenting related measures over the lifetime of the inventors. This database has 1,350,802 patent-firm pair observations and is the starting point to identify the employer of the inventor.

I begin by splitting patents in the Duke database into two groups based on whether they are assigned to a single assignee (A) or multiple assignee (B). Hence, group A consists of patents which are either single-inventor and single assignee or, multiple-inventors and single-assignee. In either case, the assignee of the patent for a given inventor is clearly identified. Group B is then further sub-divided into group B1 if it is filed with a single inventor or B2 if there are multiple inventors. So, group B1 consists of patents with single-inventor and multiple-assignees while, group B2 consists of multiple-inventors and multiple-assignees. For patents in group B1, I check if there are other patents for the given inventor from group A in the same application year and if there is a match, I then assign the assignee as the primary assignee for that inventor. If no match is found from group A, I check if the inventor can be matched to one of the assignees based on geographic location. However, using headquarter location from Compustat will give erroneous matches as Compustat provides the latest location of the headquarter for a firm. I use the historical location information (Gao et al., 2021) for matching the inventor location to the assignee location in the year of application of the patent. If no match can be found or there are multiple matches then, I drop that inventor from my sample as the assignee is ambiguous, otherwise I pick the matched assignee as the primary assignee to the inventor. For group B2, I follow the same steps as above and look at both the patents in group A and B1 to identify a unique primary assignee. As before if no clear match is found, I drop the inventor from the sample.

Once, all the patents of an inventor have been uniquely matched to a single primary assignee, I proceed to tally the number of unique assignees for an inventor in each application year. If there is a single unique assignee in a given application year then, I have an unambiguous employer of that inventor. If there are multiple assignees for an inventor in a given year, I select the assignee that has the highest number of patents for the inventor. In case of ties, I look at the employer from the previous year. If an employer was identified in the previous year, I then select that assignee as the employer for the inventor in the current year. If no assignee was clearly established, then I drop the inventor from the sample. I am now left with an inventor-dataset which has a unique employer identified to an inventor for each application year. At the end of this identification process, I am left with 1,158,745 observations of an inventor paired with the employer firm in an application year.

Next, I fill in gap years between patent applications for the inventors. If the employer is the same between two patent application years, then the inventor is assumed to have been working at the same employer in the intermediate years. If the employers are different, then I select the midpoint (M) between the application years as the last year the inventor worked for the first employer. The inventor is assumed to be working for the second employer from M+1 onwards. For two application years, Y1 and Y2, the midpoint M is calculated as M = floor (A1 + 0.5*[A1+A2]). This step removes inventors who only have a single application year in the sample period and ensures that for any inventor in the sample I can assign an ending year to their employment history.

2.3 Measuring inventor turnover

Once the inventor and employer firm have been identified, I can aggregate the inventors at the firm level. This allows me to add in firm level RFOs and other firm specific information. To study the effectiveness of RFOs for inventor retention, I need to define a measure to capture inventor retention at the firm. To do this, I define a measure to capture the rate of change of inventor employment at a firm relative to the average size of employment at the firm. Following existing literature in this area (Aldatmaz et al. 2018), I choose turnover as my measure, to study the effect of RFOs on inventor retention. I define inventor turnover, *Turnover,* as:

$$Turnover_{i,t} = \frac{\max(0,\ H_{i,t} - [E_{i,t} - E_{i,t-1}])}{0.5 \times (E_{i,t} + E_{i,t-1})} \tag{1}$$

where $Turnover_{i,t}$ is the turnover measure for firm i at time t, $H_{i,t}$ is the number of new inventor hires at firm i over time period t, $E_{i,t}$ is the total number of inventors employed at firm i at the end of time period t. An inventor is identified as being hired in the year it makes its first patent application for the firm. This measure allows me to see how inventor employment changes over a period of time relative to the average level of inventor employment at the firm during this period. A larger (smaller) number would mean that more (less) inventors left the firm during a given period relative to the inventor employment level.

From Panel A of Table 1, I see that on average *Turnover* is around 23.2% with a median figure of 12.2% for 9,475 firm-year observations. The lower observation count compared to the ExecuComp sample is the result of firms not having any innovative output (patenting activity) or inventors being dropped due to ambiguity. Looking at the hiring data I see that firms on average hire around 12 inventors each year, with a median figure of 2 hirings each year. The average employment level of inventors is approximately 81 inventors, with a median figure of 17. So, on average firms are growing around 14.5% (11.81/81.44) with the typical firm growing around 11.76% (2/17) though new hires. Compared to the turnover figures from earlier, there is net outflux of talent on average.

2.4 Inventor movement between firms

I also look at the inventors on an individual level, as any discussion of RFOs as a retention tool must ensure that inventors value RFOs as an important decision-making tool when it comes to the decision of leaving or staying with the firm. I separate inventors into two groups based on whether the change in inventor employment is a result of MA activity and or not. I focus on the inventors who change firms not as the result of any MA activity, to see what role RFOs play in their decision process. In my sample, I identify 4,582 such moves where an inventor changes employment. I take inventors who change firms as my treatment group. I take the group of inventors who never change firms as my non-treatment group. I use propensity score matching to match the inventors from my treatment group to 5 inventors from my non-treatment group on the last year of employment, industry, and firm size, along with inventor characteristics such as lifetime patents, lifetime citations and measures of breakthrough innovation used in other studies (e.g., Balsmeier, Fleming and Manso, 2017; Gao, Hsu and Li, 2018; Acemoglu, Akcigit and Ceilk, 2020; Byun, Oh and Xia, 2020; Lin, Liu and Manso, 2020). For each inventor who moves, I calculate the average RFOs per employee at the old firm in the 3 years before the last year of employment. Similarly, I also calculate the average RFO per employee at the new firm for the first 3 years of employment. I use RFOs per employee here as I am working with data at the individual level, not the firm level, and this helps to ensure my level of observation is consistent. I do a similar calculation for inventors in my control group using the last year of employment of the treated inventor for my calculation purposes.

From Panel B of Table 1, I see that after a change in employment the inventors end up with almost a 203% (19.78/6.52-1) increase in RFOs granted at the new firm. In dollar terms this an increase of $13,260. I believe this number is under-reported as there is no reason to expect all employees of the firm to be granted RFOs. As such, the true increase in RFOs received as a result of a move would be much higher. However, RFO per employee can still be used as a proxy for the true RFOs received by the inventors and would only bias my results negatively. For my control group of matched inventors, I see no such increase in RFOs per employee. Hence, there is clear indication that RFOs play a part in the inventor's decision to change firms which I explore further in the next section.

The other variables in Panel B of Table 1 provides an overview of the characteristics of the inventors in my sample. The average inventor has an active lifespan, measured as the number years between the first patent application and last patent application of 8.61 years and has almost 8.40

patents. These patents have together received on average around 10.60 citations, with citations being adjusted for truncation-lag using a fixed-effect approach (Hall, Jaffe and Trajtenberg, 2001). As a measure of the quality of these patents I use a subset of the measures for breakthrough innovation namely Top10% (1%) patents which is defined as a patent in the top 10% (1%) of the citation-distribution of all applied patents in the year of application. I measure the number of such Top10% (1%) patents for an inventor over their lifetime and see that inventors in my sample have on average about 1.29 (0.13) such patents.

3 Empirical methodology

Given that firms issue RFOs for retention purposes and the use of RFOs is more for firms with larger investment in knowledge capital and higher innovation output, as I showed in chapter I, I devise several tests to ascertain the effectiveness of such grants to retain the key personnel involved, namely inventors employed at these firms.

Firstly, I hypothesize that if the firm is making RFO grants there is a contemporaneous reduction in inventor turnover in the year of grant. I use the contemporaneous year for two reasons. First, if these RFO grants fail to retain inventors in the year of grant, then there is very little reason for firms to continue issuing such options. Second, given that RFOs are typically viewed as a form of delayed compensation, I expect that retention should be achieved immediately following the grant of such RFOs as inventors need to stick around to gain any benefit from the options granted. Therefore, to be an effective retention tool RFOs should be effective in reducing inventor turnover in the year of their grant and help with retention. To this end, I run the following regression:

$$Turnover_{i,t} = \alpha + \beta \times RFO_{i,t} + \gamma \times Turnover_{i,t-1} + Controls + \varepsilon_{i,t} \qquad (2)$$

A negative relation between contemporaneous RFOs and inventor turnover would help establish the first support for RFOs as an effective tool in helping retain inventors. I include the lagged inventor turnover to account for any persistent trend in employment at the firm. Control variables are included, and the full list and definitions of all control variables are in the Appendix. These variables such as firm size, industry, leverage, past performance, and stock return volatility are included to control for firm characteristics that may influence a firm's inventor turnover. All control variables used here and hereafter are lagged by one year.

Secondly, given the widespread use of RFOs among firms involved in heavy R&D activities, it would make little sense that RFO grants have only a passing effect. As R&D is not a short-term process and there is some time-gap till it bears fruit, there is good reason why firms would pay attention to their inventor turnover rate beyond the year of grant. If there is little in the way of inventors to leave after the year of grant, then RFOs would be a very ineffective way to retain inventors, and firms would learn very quickly that RFOs are not the right tool for long-term inventor retention. Further, it is found from other studies that RFOs are only effective at retaining all employees till around 3 years when they have completely vested (Aldatmaz et al., 2018). Given all this, my question is whether RFOs are effective in retaining inventors beyond the year of grant and whether there is a point when their effectiveness diminishes. To test this, I run the following regression:

$$Turnover_{i,t} = \alpha + \sum_{k=0}^{5} \beta_k \times RFO_{i,t-k} + Controls + \varepsilon_{i,t} \qquad (3)$$

This lagged regression will help me establish whether inventors are effectively retained through use of RFOs in the long run, or they simply leave once the options are vested thereby making RFOs only a short-term tool for retaining inventors.

Finally, any discussion of RFOs as a retention tool is incomplete without establishing that RFOs are an important factor in an individual inventor's decision to stay or leave the firm. To test out whether inventors at the individual level care about RFOs I look at inventors who leave one firm and join another during their lifetime. Using the sample of treated and control inventors defined earlier, I run the following logistic regression:

$$Outgoing_i = PreRFO_i + PostRFO_i + Controls + \varepsilon_i \qquad (4)$$

where $Outgoing_i$ is a dummy variable for inventor i which is 1 for treated group and 0 for control group, $PreRFO_i$ is the average RFO per employee at the firm over the 3 years before the last year the inventor works there and is a proxy for the amount of RFOs the inventor receives, and $PostRFO_i$ is the average RFO per employee at the new firm over the first 3 years of joining the firm and is a proxy for the amount of RFOs the inventor would receive if they joined. I expect that higher $PreRFO_i$ should reduce the probability that the inventor leaves their current firm and higher $PostRFO_i$ should increase the probability that the inventor leaves their current firm.

4 Empirical findings

4.1 Effect of RFOs on inventor turnover

One of the driving forces behind corporate innovation is the workforce employed by the firm. Research & development is a drawn-out process and inventors are the key personnel involved in seeing the projects to fruition. As such, it is in the firm's best interest to ensure such key employees continue to work for the firm and don't leave in the middle of the R&D project. RFOs have been used by firms for this task with more innovative firms making heavy use of such RFO grants. The question that then remains is whether RFOs actually help to retain these inventors. To answer this question, I look at the inventor turnover at firms and the effect of issuing RFOs. Inventor turnover helps to capture the overall rate of attrition for inventors employed at the firm. The null hypothesis is that RFO grants have no impact on inventor turnover. It would be hard to argue that RFOs are worthwhile from a firm's perspective as a retention tool if it cannot prevent inventors from leaving the firm.

To test this empirically, I run a regression of *Turnover* against the *RFOs* issued by the firm as described in Equation (2). I also include the lagged value of *Turnover* for the firm to take care of any serial correlation. This helps to ensure that any observed relationship between *Turnover* and *RFOs* is free from short-run events (mass-firings/resignations) at the firm. Results of the regressions are summarized in Table 2.

Table 2

As shown in column (1) of Table 2, use of RFOs indeed helps to reduce the inventor turnover at the firm. The co-efficient of RFOs is negative and significant at the 1% level of significance. In particular, a one-standard deviation increase in RFOs from its average level

($14.88 million) reduces inventor turnover by 36% from its average level (0.232). The impact is substantial and clearly shows that RFOs have a strong impact in reducing inventor turnover. The relationship continues to be strong and significant after controlling for any serial correlation, column (2). Unsurprisingly, lagged inventor turnover has a positive and significant impact on current turnover which indicates that any firm specific reason for inventor attrition continues to have a lingering effect. As a further test of the strength of the relationship, I control for firm specific characteristics, firm and year fixed effect and clustering the standard errors at the firm level, column (5). The effect of RFOs remains statistically significant at the 1% level with an economic impact of reducing inventor turnover by 15%. The results here clearly show that granting of RFOs has the immediate effect of preventing inventors from leaving the firm and the effect is substantial.

4.2 Inventor turnover and lagged RFOs

The effect of retaining inventors following RFO grant is a positive indicator towards RFOs being an effective retention tool. However, it wouldn't be very useful if the use of RFOs only leads to a short-term effect, with inventors leaving in the years following the RFO grant. For RFOs to be an effective tool, their effect needs to persist beyond the year of grant. Aldatmaz et al., 2018, have shown that RFOs tend to have a short-lived effect with employees leaving around 3 years following the grant of RFOs which marks the average time when the options have fully vested. They however looked at the overall level of employment at the firm. The insight that RFOs tend to be used more by innovative firms and that the target for retention is a subset of the employees, namely inventors, suggests we have to look at the inventor turnover following an RFO grant to evaluate the effectiveness of RFOs as a retention tool. For this I make use of Equation (3). I look all the way back to 5 years as R&D projects at firms can have a long lifespan and for RFOs to be effective it needs to be able to keep the inventors at the firm over a longer time span. Further, the average vesting period for options are three to four years (Oyer and Schaefer, 2005) and I believe 5 years is an appropriate time period to cover the effects of RFO grants. The results of running the regression for Equation (3) are given in Table 3.

Table 3

From column (1), I see that the issuance of RFOs has a persistent effect of reducing inventor turnover all the way back to 2 years since RFO grant. The co-efficient on lagged RFOs for lags 1 and 2 are all negative and statistically significant at the 1% level. I also see that the effect of RFOs is positive and statistically significant at the 1% level for lags at year 4 and 5. This might suggest that RFOs help to retain inventors at the firm till the time the options vest, with the inventors then moving away from the firm. However, once I control for firm specific characteristics and include firm and year fixed effect with standard errors clustered at the firm level, given in column (4), the moving away effect weakens. The co-efficient on lagged RFOs remains negative till lag 3, with lagged years 1 and 3 being statistically significant at the 5% level. The co-efficient for RFOs at lags 4 and 5 lose their significance and aren't statistically different from zero. This result shows that overall RFOs are effective at retaining inventors over an extended period of time, going all the way to 5 years since grant. This further helps to shed light on why firms issue RFOs when in general employees leave around the 3-year mark. The reason is tied to the target employees for these RFOs, which are the personnel involved in R&D and RFOs are highly effective at retaining this specific subset of employees.

To ensure that my findings are not a result of the extended period of study of lagged RFO grants and the correlation between the lagged terms themselves, I repeat my results for the window containing 3 lags similar to other studies (Aldatmaz et al, 2018). The results are in Table 4.

Table 4

I find similar results as presented before with RFO grants at lag 1 being negative and statistically significant at the 1% level, column (4). The RFO co-efficient at lag 3 is negative but statistically insignificant. Overall, the results in Table 4 continues to paint a similar picture as before. Combined with my results from Table 3, I see that having more lags in the regression helps to show the long-lasting impact of RFOs on inventor retention. So, unlike the case for general employees at the firm, RFOs are very effective at retaining inventors over long time periods.

4.3 Individual inventors and RFOs

Up to this point I have focused on the effectiveness of RFOs as a retention tool for the firms when it comes to retaining inventors. I also want to look at the inventor side of the story to see if individual inventors treat RFOs as an important factor in making employment decisions. To this effect, I use the changes in inventor employment in my sample to figure out how much of a role RFOs play in deciding whether to continue with an existing employer or move to a new one. In my sample of inventors, I have 4,582 occurrences of inventors moving from one firm to another, which forms the treatment group. This number excludes inventors who have a change of employer due to MA activity. For each inventor that moves, I find 5 matching inventors with replacement from the sample of inventors who only ever work for a single firm. I match inventors on the industry, specifically the 2-digit sic code, the last year the inventor works for the firm and the size of the firm proxied by the log of sales. Further, to ensure the inventors are similar in terms of talent and productivity when they move, I use the length of time that they have been active, the cumulative patent count, the patent count in the 3 years before a move, average citations per patent and measures of breakthrough innovation captured through the cumulative count of top 10% patents and top1% patents up to the last year of employment. I take the log of all the patent related measures reduce the effect of any outliers. The result of this matching process is presented in Table 5.

Table 5

I get a good match between my treatment group and control group with the difference in measures that I match on being statistically insignificant.

To see if RFOs impact the individual inventor's decision to stay or leave I define a dummy variable, called Outgoing, which is 1 for the inventors who are part of the treatment group and 0 if they are part of the control group. I look at the average RFO per employee 3 years before and after the inventor leaves the firm, measured through Pre-RFO and Post-RFO variables. I run a logistic regression of Outgoing against the pre and post RFO measures with the null hypothesis of no impact of either measure. The result of the logistic regression is presented in Table 6.

Table 6

Column (1) of Table 6, shows that Pre-RFO is negative and statistically significant at the 1% level of significance. This means that inventors are less likely to leave a firm if the firm offers more RFOs per employee. As mentioned before, this is a weaker result as not all employees at the firm receive RFO grants. Hence, I believe the actual effect to be stronger. Also, from column (1) I see that Post-RFO is positive and significant at the 1% level of significance. This is unsurprising as RFOs are also used to attract talent. I thus can conclude that RFO grants reduce the probability that the inventor leaves the firm and thus plays a role in the individual inventor decision to stay or leave. In a separate set of results, I run a marginal effect at the mean regression to make it easier to interpret the economic significance of the results here. There I find that a one standard deviation increase in Pre-RFO ($14,307) reduces the probability that the inventor leaves the firm by 1.66%. The rest of the columns of Table 6 show the robustness of the results to firm specific characteristic, industry and year fixed effects and clustered standard errors at the industry and firm level. The results continue to hold under these added model specifications thus showing that RFOs indeed play an import role in the inventor's decision to stay or leave the firm. I also ran a probit model, and the results are very similar to the ones presented here and have been excluded for brevity.

5 Robustness tests

5.1 Option expensing under FAS123R

The passage and implementation of the FAS123R has led to two exogenous shocks to the use of stock options in the compensation of top executives and rank-and-file employees. For one thing, it changes the way firms report their stock option grants to the public. Of the numerous changes, the one most relevant to the present study is that firms no longer report each top executive's option grant as a percentage of the firm's total number of options granted that year. It is no longer possible to calculate the total amount of stock options each firm grants to their rank-and-file employees using the ExecuComp database (which is built from annual reports firms file with the SEC). Instead, I use another data source, Compustat, that does report the total amount of stock options granted by the firm each year. This change may lead to inconsistencies in my estimate of the total amount of RFOs before and after the implementation of FAS123R. This is however only a minor concern as I have verified that the potential inconsistencies are quite minimal (as discussed in Section 2.1).

More importantly, the implementation of FAS123R has led to a subsequent migration from stock options to restricted stock (and performance-vested equity pay in general) in the compensation of top executives and rank-and-file employees (Hayes, Lemmon and Qiu, 2012; Murphy, 2012; Edmans, Gabaix and Jenter, 2017). It is therefore not a surprise that the use of RFOs for employee retention purposes is impacted negatively by the implementation of FAS123R in 2006. There is a reduction in the use RFOs across firms which makes it possible to evaluate the causal relationship between use of RFOs and their effectiveness as a retention tool. Specifically, FAS123R creates an exogeneous shock which directly affects RFO grants through a reduction in their use. Hence FAS123R gives me an opportunity to study how inventor turnover changes following FAS123R adoption as inventors now - find themselves in an environment where the overall RFO grant levels have declined. I start by regressing inventor turnover on an indicator variable *FAS123R*, which takes a value of 1 if the year is 2006 or after and 0 otherwise. I also include an interaction term between the RFOs issued and the *FAS123R* dummy. The results of the regression are in Table 7.

Table 7

I see from column (1) of Table 7 that the co-efficient on the *FAS123R* dummy is positive and statistically significant at the 1% level. This indicates that there was an increase in inventor turnover following the implementation of FAS123R. Looking at the interaction term I see that offering more RFOs in the post-FAS123R period leads to a much stronger reduction in inventor turnover than in the pre-FAS123R period. For a one standard deviation increase in RFOs this leads to a 37% (0.2336/0.6257) reduction in inventor turnover in the post-FAS123R period. Although this might not seem to be much different from my results earlier, this reduction happens in the post-FAS123R period where the turnover levels (0.6257) are much higher than the average level (0.232) in my sample. The rest of the columns, (2) – (5), tests my hypothesis under various model specifications to control for firm specific characteristics, fixed effects and clustered standard errors. As FAS123R was a shock to the use of RFOs and there is very little reason to believe that the inventor turnover should be directly impacted by an accounting change such as FAS123R implementation in 2006, I conclude that the increase in inventor turnover in the post-FAS123R period is a result of the reduction in RFOs, thus establishing a causal link between inventor turnover and RFO grants. The results above do however seem to suggest that the switch to restricted stock awards doesn't seem to have the same impact on inventor retention as stock options do. If these two instruments were the same in the eyes of the recipient, then FAS123R should have no impact on inventor turnover. Furthermore, the stronger desire for stock options as evidenced by the greater decline in inventor turnover post-FAS123R, seems to point to a further investigation of the importance of restricted stock and RFOs and their substitutability.

6 Conclusions

Are RFOs an effective tool for employee retention? It depends on what type of employee we are trying to retain. For employees involved in R&D, RFOs are a very effective tool at inventor retention. Unlike the case for the average employee at the firm, inventor turnover sees a stark decline not only following an option grant but also 5 years into the past. This observation makes sense given that the use of RFOs are positively correlated with the corporate innovation going on at the firm. I also show the importance of such options to the inventors involved. Individual inventors pay strong attention to the amount of RFOs that they can get, and this is highlighted in their decision to stay or leave the firm. Finally, the importance of RFOs at retaining inventors takes on greater significance when I look at periods when issuing RFOs are very costly like the post FAS123R adoption. Under such a setting the impact of RFOs at reducing inventor turnover becomes even greater and highlights the effectiveness of RFOs as a retention tool.

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8 Tables

Table 1

Descriptive Statistics

This table reports summary statistics of inventor level and firm level variables for the period 1992-2010. Turnover is defined as the number of inventors who left the firm in a giver year divided by the average employment level during the year. Hires is the number of inventors hired by the firm each year. Inventors is the number of inventors employed by the firm each year. RFO is defined as the total value of options granted to all employees other than the top executives, in $ millions and are estimated by subtracting stock options granted to top executives from the total amount of options granted to all employees. Lifetime Patent is the total patents applied for by the inventor over their lifetime, with lifetime being defined as the period from the first patent application till the last patent application. Lifetime Total Citations is the total citations received by the inventor, adjusted for truncation lag using a fixed effect approach, over their lifetime. Lifetime Top10% (1%) Patents is the total number of patents of the inventor that are in the top 10% (1%) of the patent citation distribution of all patents applied that year over the lifetime of the inventor. Years Active is the number of years between the first patent application and the last patent application for an inventor. Pre-RFO (Post-RFO) is the average value of RFO divided by the number of employees, in 000's dollars, over the 3 years before (after) the last year the inventor works for the firm. For each inventor that leaves a firm, I use propensity score matching to find 5 similar inventors as a control group. Details of control variables for firm characteristics are in Appendix A. All continuous variables are winsorized at 1% and 99%.

Panel A: Firm Level								
	Mean	SD	Min	Q1	Median	Q3	Max	Obs
Turnover	0.232	0.313	0.000	0.000	0.122	0.293	1.500	9,475
Hires	11.809	29.438	0.000	0.000	2.000	9.000	207.000	9,695
Inventors	81.435	190.525	1.000	5.000	17.000	61.000	1,287.000	9,695
RFO	14.882	40.767	0.000	0.000	3.325	10.611	300.931	35,432
Leverage	0.186	0.175	0.000	0.024	0.153	0.297	0.766	35,283
Interest Burden	0.208	0.207	0.000	0.070	0.151	0.274	1.000	35,276
Book-to-Market	0.670	0.273	0.116	0.464	0.680	0.887	1.354	35,280
R&D/Sales	0.102	0.297	0.000	0.004	0.021	0.088	2.270	29,731
Log (Sales)	6.953	1.625	2.795	5.860	6.892	8.025	10.881	35,283
Log (Employees)	1.427	1.676	-2.797	0.313	1.457	2.559	5.289	35,283
Past stock performance	0.209	0.604	-0.790	-0.123	0.123	0.395	3.365	35,276
Stock return volatility	0.116	0.066	0.031	0.071	0.100	0.144	0.382	35,254
Panel B: Inventor Level								
Lifetime Patent	8.393	9.672	2.000	3.000	5.000	10.000	62.000	217,458
Lifetime Total Citations	10.599	17.119	0.000	1.887	4.644	11.286	129.957	217,458
Lifetime Top10% Patents	1.249	2.377	0.000	0.000	0.000	1.000	17.000	217,458

Lifetime Top1% Patents	0.125	0.486	0.000	0.000	0.000	0.000	4.000	217,458
Years Active	8.609	6.378	2.000	4.000	7.000	12.000	29.000	217,458
Pre-RFO (Treatment)	6.523	14.307	0.000	0.519	1.429	5.217	175.954	4,582
Post-RFO (Treatment)	19.784	33.664	0.000	0.971	5.163	20.050	192.614	4,582
Pre-RFO (Control)	7.135	16.564	0.000	0.459	1.159	4.683	145.383	22,906
Post-RFO (Control)	7.439	13.216	0.000	0.884	2.381	6.781	135.732	22,906

Table 2

Inventor turnover and rank-and-file option grants

This table reports the regression results of inventor turnover on rank-and-file option grants (RFOs). *Turnover* is defined as the number of inventors who left the firm in a giver year divided by the average employment level during the year. *RFO* is defined as the total value of options granted to all employees other than the top executives, in $ millions and are estimated by subtracting stock options granted to top executives from the total amount of options granted to all employees. $Turnover_{-1}$ is the value of *Turnover* lagged by 1 period. Log transformation, ln(1+*x*), is applied to *RFO* to reduce the impact of outliers. Details of control variables for firm characteristics are in the Appendix A. All continuous variables are winsorized at 1% and 99%. Numbers in parenthesis are *t*-statistics and ***, ** and * denote 1%, 5% and 10% statistical significance, respectively.

	Dependent variable:				
	Turnover				
	(1)	(2)	(3)	(4)	(5)
Log (RFO)	-0.0223***	-0.0131***	-0.0240***	-0.0096***	-0.0096***
	(-11.7566)	(-7.2200)	(-10.5661)	(-3.7003)	(-3.5274)
$Turnover_{-1}$		0.6165***	0.5715***	0.0753***	0.0753***
		(22.7850)	(25.2107)	(3.1909)	(3.0897)
Leverage			-0.0265	0.0345	0.0345
			(-1.1289)	(1.2069)	(1.1251)
Interest Burden			0.0340*	0.0562**	0.0562**
			(1.8593)	(2.3218)	(2.0430)
R&D/Sales			0.0327***	-0.0205	-0.0205
			(3.3735)	(-1.3375)	(-1.3584)
Book-to-Market			0.0005	0.0522**	0.0522**
			(0.0313)	(2.4807)	(2.2321)
Log (Sales)			0.0660***	0.0148	0.0148
			(11.7803)	(1.3758)	(1.3419)
Log (Employees)			-0.0460***	-0.0046	-0.0046
			(-8.0470)	(-0.4253)	(-0.4460)
Past stock performance			-0.0202***	0.0010	0.0010
			(-4.0947)	(0.2067)	(0.2049)
Stock return volatility			0.0547	0.0236	0.0236
			(1.0648)	(0.3556)	(0.3244)
Constant	0.2775***	0.1546***	-0.2111***		
	(47.4785)	(26.9074)	(-6.6049)		
Firm FE	X	X	X	YES	YES
Year FE	X	X	X	YES	YES

Clustered SE	X	X	X	X	FIRM
Observations	9,404	9,154	9,130	9,130	9,130
Adjusted R^2	0.0117	0.2139	0.2354	0.4286	0.4286

Table 3

Change in inventor turnover for lagged rank-and-file option grants with up to 5 lags

This table reports the regression results of inventor turnover on both contemporaneous and lagged values of rank-and-file option grants (RFOs). *Turnover* is defined as the number of inventors who left the firm in a giver year divided by the average employment level during the year. *RFO* is defined as the total value of options granted to all employees other than the top executives, in $ millions and are estimated by subtracting stock options granted to top executives from the total amount of options granted to all employees. RFO_{-t} is the value of *RFO* lagged by t periods. Log transformation, ln(1+*x*), is applied to all *RFO* measures to reduce the impact of outliers. Details of control variables for firm characteristics are in the Appendix A. All continuous variables are winsorized at 1% and 99%. Numbers in parenthesis are *t*-statistics and ***, ** and * denote 1%, 5% and 10% statistical significance, respectively.

	Dependent variable:			
	Turnover			
	(1)	(2)	(3)	(4)
Log (RFO)	-0.0382***	-0.0369***	-0.0087**	-0.0087**
	(-9.5912)	(-8.9262)	(-2.3721)	(-2.3017)
Log (RFO_{-1})	-0.0326***	-0.0338***	-0.0081**	-0.0081**
	(-7.2518)	(-7.4670)	(-2.0835)	(-2.2023)
Log (RFO_{-2})	-0.0181***	-0.0202***	-0.0049	-0.0049
	(-4.1814)	(-4.5757)	(-1.2762)	(-1.2943)
Log (RFO_{-3})	-0.0059	-0.0090*	-0.0087**	-0.0087**
	(-1.2432)	(-1.9061)	(-2.1892)	(-2.2942)
Log (RFO_{-4})	0.0213***	0.0153***	-0.0011	-0.0011
	(4.3616)	(3.1537)	(-0.2632)	(-0.2579)
Log (RFO_{-5})	0.0520***	0.0420***	0.0049	0.0049
	(11.8139)	(9.6593)	(1.3230)	(1.2839)
Leverage		-0.0500	-0.0021	-0.0021
		(-1.4786)	(-0.0467)	(-0.0432)
Interest Burden		0.0450	0.0551	0.0551
		(1.6026)	(1.3828)	(1.2102)
R&D/Sales		0.0481***	-0.0184	-0.0184
		(2.9456)	(-0.5516)	(-0.6117)
Book-to-Market		0.0224	0.0393	0.0393
		(0.9293)	(1.1803)	(1.1096)
Log (Sales)		0.0751***	0.0121	0.0121
		(8.2736)	(0.5282)	(0.5476)
Log (Employees)		-0.0451***	0.0048	0.0048
		(-5.2088)	(0.2007)	(0.2263)

Past stock performance		-0.0189**	0.0010	0.0010
		(-1.9975)	(0.1297)	(0.1301)
Stock return volatility		0.0666	-0.0192	-0.0192
		(0.8106)	(-0.2021)	(-0.1898)
Constant	0.3539***	-0.0891*		
	(37.7502)	(-1.6571)		
Firm FE	X	X	YES	YES
Year FE	X	X	YES	YES
Clustered SE	X	X	X	FIRM
Observations	5,428	5,411	5,411	5,411
Adjusted R^2	0.1187	0.1386	0.4707	0.4707

Table 4

Change in inventor turnover for lagged rank-and-file option grants with up to 3 lags

This table reports the regression results of inventor turnover on both contemporaneous and lagged values of rank-and-file option grants (RFOs). *Turnover* is defined as the number of inventors who left the firm in a giver year divided by the average employment level during the year. *RFO* is defined as the total value of options granted to all employees other than the top executives, in $ millions and are estimated by subtracting stock options granted to top executives from the total amount of options granted to all employees. RFO_{-t} is the value of *RFO* lagged by t periods. Log transformation, ln(1+*x*), is applied to all *RFO* measures to reduce the impact of outliers. Details of control variables for firm characteristics are in the Appendix A. All continuous variables are winsorized at 1% and 99%. Numbers in parenthesis are *t*-statistics and ***, ** and * denote 1%, 5% and 10% statistical significance, respectively.

	Dependent variable:			
	Turnover			
	(1)	(2)	(3)	(4)
Log (RFO)	-0.0443***	-0.0418***	-0.0087***	-0.0087***
	(-12.7727)	(-11.5707)	(-2.7724)	(-2.7203)
Log (RFO_{-1})	-0.0250***	-0.0286***	-0.0098***	-0.0098***
	(-6.4508)	(-7.3014)	(-2.9456)	(-3.0006)
Log (RFO_{-2})	0.0027	-0.0059	-0.0018	-0.0018
	(0.7120)	(-1.5251)	(-0.5492)	(-0.5476)
Log (RFO_{-3})	0.0391***	0.0233***	-0.0016	-0.0016
	(11.5772)	(6.7393)	(-0.4988)	(-0.4987)
Leverage		-0.0409	0.0132	0.0132
		(-1.3726)	(0.3555)	(0.3230)
Interest Burden		0.0803***	0.0662**	0.0662*
		(3.2976)	(2.0858)	(1.7842)
R&D/Sales		0.0534***	-0.0270	-0.0270
		(3.8834)	(-1.1356)	(-1.1717)
Book-to-Market		-0.0019	0.0458*	0.0458
		(-0.0918)	(1.7162)	(1.5314)
Log (Sales)		0.0926***	0.0126	0.0126
		(11.6660)	(0.7426)	(0.7600)
Log (Employees)		-0.0527***	0.0019	0.0019
		(-7.1365)	(0.1110)	(0.1216)
Past stock performance		-0.0189***	0.0008	0.0008
		(-2.5891)	(0.1275)	(0.1294)
Stock return volatility		0.1238*	-0.0031	-0.0031
		(1.7589)	(-0.0377)	(-0.0345)

Constant	0.3332***	-0.2097***		
	(41.0021)	(-4.5910)		
Firm FE	X	X	YES	YES
Year FE	X	X	YES	YES
Clustered SE	X	X	X	FIRM
Observations	6,960	6,941	6,941	6,941
Adjusted R^2	0.0584	0.0979	0.4447	0.4447

Table 5

Distributional difference between treatment and control inventors

This table reports the means of inventor characteristics after propensity score matching. *Treatment* group consists of inventors that move from one firm to another during their lifetime, with lifetime being defined as the period from their first patent application to their last patent application. *Non-treatment* group consists of inventors who work only at one firm during their lifetime. *Control* group consists of inventors who were matched to *Treatment* group inventors. Each inventor in the *Treatment* group is matched to 5 inventors in the *Non-treatment* group with replacement. Matching is done on 2-digit sic code for industry, the last year the inventor worked for their firm, size of the firm and the variables listed below. *Years Active* is the number of years between the first patent application and the last patent application for an inventor. *Cumulative Patent Applied* is the sum of patents applied for by the inventor till the last year the inventor works for the firm. *Patents Applied Last 3 Years* is the sum of patents applied for by the inventor in the 3 years before the last year the inventor works for the firm. *Cumulative Top 10% (1%) Patents* is the sum of the number of patents that are in the top 10% of the patent citation distribution of all patents applied that year by the inventor till the last year the inventor works for the firm. *Average Citations per Patent* is the average of the citations, adjusted for truncation lag using a fixed effect approach, received by patents of the inventor till the last year the inventor works for the firm. *Sales* is the total sales each year.

Support	Control	Treatment	Difference	p.value
Log (Years Active)	2.197	2.198	-0.001	0.862
Log (Cumulative Patent Applied)	1.767	1.779	-0.012	0.358
Log (Patents Applied Last 3 Years)	0.900	0.890	0.010	0.433
Log (Cumulative Top 10% Patents)	0.526	0.519	0.007	0.549
Log (Cumulative Top 1% Patents)	0.083	0.079	0.004	0.371
Log (Average Citations per Patent)	0.761	0.750	0.011	0.109
Log (Sales)	9.271	9.285	-0.014	0.608

Table 6

Inventor propensity to leave and rank-and-file option grants

This table reports the results for a logistic regression of inventor propensity to leave and rank-and-file option grants (RFOs). *Outgoing* is a dummy variable that is 1 if the inventor moves from one firm to another. It is 1 for inventors in the *Treatment* group and 0 for inventors in the *Control* group matched through propensity score matching. Pre-RFO (Post-RFO) is the average value of RFO divided by the number of employees, in 000's dollars, over the 3 years before (after) the last year the inventor works for the firm. Details of control variables for firm characteristics are in the Appendix A. All continuous variables are winsorized at 1% and 99%. Numbers in parenthesis are *t*-statistics and ***, ** and * denote 1%, 5% and 10% statistical significance, respectively.

	Dependent variable:				
	Outgoing				
	(1)	(2)	(3)	(4)	(5)
Pre-RFO	-0.020***	-0.017***	-0.018***	-0.018***	-0.018***
	(-10.976)	(-8.262)	(-8.177)	(-3.009)	(-3.009)
Post-RFO	0.032***	0.039***	0.044***	0.044***	0.044***
	(33.886)	(33.864)	(33.235)	(6.657)	(6.657)
Leverage		-1.439***	-2.108***	-2.108	-2.108
		(-7.305)	(-9.384)	(-1.187)	(-1.187)
Interest Burden		1.486***	1.620***	1.620**	1.620**
		(8.096)	(7.597)	(2.084)	(2.084)
R&D/Sales		-0.197	-0.300	-0.300	-0.300
		(-1.016)	(-1.355)	(-0.515)	(-0.515)
Book-to-Market		1.452***	1.783***	1.783***	1.783***
		(13.414)	(14.509)	(5.630)	(5.630)
Log (Sales)		0.069	-0.009	-0.009	-0.009
		(1.579)	(-0.148)	(-0.028)	(-0.028)
Log (Employees)		-0.010	0.151**	0.151	0.151
		(-0.194)	(2.258)	(0.434)	(0.434)
Past stock performance		-0.106**	0.025	0.025	0.025
		(-2.441)	(0.526)	(0.286)	(0.286)
Stock return volatility		-0.074	-0.030	-0.030	-0.030
		(-0.197)	(-0.059)	(-0.012)	(-0.012)
Constant	-1.847***	-3.257***			
	(-94.763)	(-13.093)			
Industry FE	X	X	YES	YES	YES
Year FE	X	X	YES	YES	YES
Clustered SE	X	X	X	INDUSTRY	INDUSTRY + FIRM

Observations	27,488	27,488	27,488	27,488	27,488
Deviance	23,299	22,658	22,451	22,451	22,451

Table 7

Impact of FAS123R on inventor turnover

This table reports the regression results of inventor turnover on rank-and-file option grants (RFOs) and implementation of FAS123R. *Turnover* is defined as the number of inventors who left the firm in a giver year divided by the average employment level during the year. *FAS123R* is an indicator variable which is 1 if the year is 2006 or after and 0 otherwise. *RFO* is defined as the total value of options granted to all employees other than the top executives, in $ millions and are estimated by subtracting stock options granted to top executives from the total amount of options granted to all employees. $Turnover_{-1}$ is the value of *Turnover* lagged by 1 period. Log transformation, ln(1+*x*), is applied to *RFO* to reduce the impact of outliers. Details of control variables for firm characteristics are in the Appendix A. All continuous variables are winsorized at 1% and 99%. Numbers in parenthesis are *t*-statistics and ***, ** and * denote 1%, 5% and 10% statistical significance, respectively.

	Dependent variable:				
	Turnover				
	(1)	(2)	(3)	(4)	(5)
Log (RFO)	-0.0001	0.0005	-0.0042**	-0.0071**	-0.0071**
	(-0.0775)	(0.3167)	(-1.9734)	(-2.4986)	(-2.5268)
FAS123R	0.4611***	0.3350***	0.3131***	0.3738***	0.3738***
	(24.4345)	(20.9049)	(16.8271)	(17.2367)	(18.3427)
Log (RFO) x FAS123R	-0.0626***	-0.0464***	-0.0346***	-0.0460***	-0.0460***
	(-6.7004)	(-5.5499)	(-3.9450)	(-4.8195)	(-4.8303)
$Turnover_{-1}$		0.4397***	0.4179***	0.2806***	0.2806***
		(17.3356)	(18.5481)	(11.5447)	(10.4373)
Leverage			0.0057	0.0818***	0.0818**
			(0.2570)	(2.6382)	(2.5396)
Interest Burden			0.0305*	0.0398	0.0398
			(1.7644)	(1.6400)	(1.5812)
R&D/Sales			0.0095	0.0202	0.0202
			(1.0040)	(1.2740)	(1.4676)
Book-to-Market			0.0472***	0.1185***	0.1185***
			(3.3305)	(5.3671)	(5.0475)
Log Sales			0.0222***	0.1058***	0.1058***
			(4.0099)	(10.4393)	(9.6687)
Log Employees			-0.0092*	-0.0435***	-0.0435***
			(-1.6556)	(-3.9151)	(-3.9428)
Past stock performance			-0.0092**	0.0078	0.0078
			(-1.9983)	(1.4838)	(1.4386)
Stock return volatility			0.1530***	0.1919***	0.1919***

			(3.1424)	(3.1652)	(3.0506)
Constant	0.1650***	0.1091***	-0.0681**		
	(37.1773)	(20.9438)	(-2.1876)		
Firm FE	X	X	X	YES	YES
Clus SE	X	X	X	X	FIRM
Observations	9,404	9,154	9,130	9,130	9,130
Adjusted R^2	0.2180	0.3052	0.3131	0.3372	0.3372

9 Appendix

9.1 List of variables and definitions

Name	Definition
RFO	Total value of options granted to all employees other than the top executives, in $ millions. RFOs are estimated by subtracting stock options granted to top executives from the total amount of options granted to all employees.
RFO_{-t}	RFO lagged by t years.
Pre-RFO	Average value of RFO divided by the number of employees, in 000's dollars, over the 3 years before the last year the inventor works for the firm.
Post-RFO	Average value of RFO divided by the number of employees, in 000's dollars, over the 3 years after the last year the inventor works for the firm.
Turnover	Turnover is defined as $\frac{max(0,[H(t) - \{E(t) - E(t-1)\}])}{0.5*[E(t) + E(t-1)]}$ where, H(t): Number of new inventor hires during period t. E(t): Number of inventors at the end of period t.
Hires	The number of inventors hired by the firm each year.
Inventors	The number of inventors employed by the firm each year.
Lifetime Patent	Total patents applied for by the inventor over their lifetime, with lifetime being defined as the period from the first patent application till the last patent application.
Lifetime Total Citations	Total citations, adjusted for truncation lag using a fixed effect approach, received by the inventor over their lifetime, with lifetime being defined as the period from the first patent application till the last patent application.
Lifetime Top10% Patents	Total number of patents of the inventor that are in the top 10% of the patent citation distribution of all patents applied that year over the lifetime of the inventor.
Lifetime Top1% Patents	Total number of patents of the inventor that are in the top 1% of the patent citation distribution of all patents applied that year over the lifetime of the inventor
Outgoing	Dummy variable which is 1 if the inventor is part of the treatment group and 0 if the inventor is part of the control group.
Years Active	Number of years between the first patent application and the last patent application for an inventor.
Cumulative Patent Applied	Sum of patents applied for by the inventor till the last year the inventor works for the firm.
Patents Applied Last 3 Years	Sum of patents applied for by the inventor in the 3 years before the last year the inventor works for the firm.

Cumulative Top 10% Patents	Sum of the number of patents that are in the top 10% of the patent citation distribution of all patents applied that year by the inventor till the last year the inventor works for the firm.
Cumulative Top 1% Patents	Sum of the number of patents that are in the top 1% of the patent citation distribution of all patents applied that year by the inventor till the last year the inventor works for the firm.
Average Citations per Patent	Average of the citations, adjusted for truncation lag using a fixed effect approach, received by patents of the inventor till the last year the inventor works for the firm.
FAS123R	An indicator variable which is 1 if the year is 2006 or after and 0 otherwise.
Leverage	Long term debt scaled by total assets.
Interest burden	The three-average average of interest expense scaled by operating income before depreciation.
R&D/Sales	The three-year average of research and development expense scaled by sales.
Book-to-market	The three-year average ratio of book value of assets over the sum of book value of liabilities and market value of equity.
Sales	Total sales each year.
Employees	Number of employees.
Past stock performance	The buy-and-hold stock return over the past 12 months.
Stock return volatility	Standard deviation of monthly stock returns in the past year.

Chapter III

III Do Managers Time Patent Filing?

Aman Khan

1 Introduction

Starting from Schumpeter's creative destruction theory (Schumpeter, 1950), a large body of economic literature (Cefis and Marsili, 2006; Audretsch, 1995), posits that innovation plays a key role for growth and survival of firms. Firms try to guard their intellectual resources by getting protection in the form of patent grants. As a result, it is natural to assume that firms should try to obtain this protection at the earliest, and therefore apply for a patent right upon completion of their innovation projects.

Given the nature of research and development, it is hardly ever possible to measure ex-ante the time to completion or set a strict deadline by which the patent production process should complete. So, it is safe to assume that the patent production function is random. Furthermore, it is reasonable to assume that firms have many such agents partaking in the patent production process, making the aggregate number of patents ready for filing in a given period more likely to be random. Finally, there is no reason to believe that any specific point in time would be more probable for the research process to complete on than any other point in time. Given these assumptions, along with the fact that firms try to get protection at the earliest, one would assume to see a more uniform distribution for patent applications throughout the year. However, I find that this is not the case, and 40% of all patent applications are filed in the last quarter of the year. This clearly hints that one or more of my assumptions above are not correct. I argue that the most likely culprit is the last one; firms are not always likely to get their protection at the earliest and I further discuss why that might be a plausible explanation.

I argue that there is a strategic element in the timing of patent applications by firms, which I denote as patent window dressing. Although existing finance literature has largely focused on window dressing by pension and mutual fund managers (Lakonishok et al.,1991; Agarwal et al., 2014), there is evidence that corporate managers engage in window dressing, too. For example, Allen and Saunders (1992) find evidence of a systematic upward window dressing adjustment in bank assets on the last day of each quarter. Chen, Cohen, and Lou (2016) demonstrate that managers of multi-segment conglomerates position their firms as part of a certain industry when that industry is more favorable than the others. Extensive evidence of earnings management is further consistent with the idea that firms window dress their accounting performance. If managers try to window dress their accounting statements, it is also possible that they will try to window dress firms' intangible assets that are relevant to market participants but are not captured by accounting statements.

If clustering of patent applications in the last quarter is truly an attempt to window dress assets, there should be a reward for managers. Existing studies show that investors do pay attention to patent applications. Kogan et al (2017) for instance, claim that firms publicize their patent application even before patent grant and investors price this news. Consequently, managers who are motivated to increase the value of their firms during certain periods, are motivated to window dress their patent applications.

I start my analysis by disentangling the window dressing explanation, according to which firms strategically time the filing of patent applications by postponing the filing of completed applications and rushing the filing of uncompleted ones, from alternative explanations. For example, firms may routinely use end of the calendar year as project deadlines (which, in turn, could be related to Christmas bonuses, work slowdowns during to winter holidays, or psychological desire to finish old projects before “new beginnings” of the new year). As a result, clustering of patent application in the last quarter may reflect some general features of organizational work planning and indicate completion of existing R&D projects that is not driven by timing.

To establish window dressing as the underlying mechanism, I perform several tests. First, I look at the quality of patents that are filed during each fiscal quarter. If firms use patent applications to window dress their R&D performance, they may choose to rush some projects instead of spending more time on polishing the application and improve its quality. Therefore, I expect the quality of fourth quarter patents to be considerably lower than patents that are filed during the other quarters. Hence, I introduce two variables that capture quality. First, the adjusted citation count (Hall, Jaffe & Trajtenberg, 2001) measures the number of citations received by a patent after correcting for truncation lag. I find that there is a significant drop in the citations received by patents filed in the 4th quarter. Next, I look at a measure of breakthrough innovation, Top10, (Byun, et. al, 2020). This indicator variable is equal to 1 if the citations received by the patent falls in the top 10% of the citations received by all patents filed each year. I then look at the probability that a given patent is a Top10 patent for a calendar quarter. These citation measures are all corrected for the truncation lag based on the fixed-effect approach by Hall, Jaffe and Trajtenberg, 2001. I select these measures as they capture the relative importance of the patents in their given cohort. The result show that patents filed in the last quarter are less likely to be breakthrough innovations. Both measures show a drop in the quality of patent applications in the last calendar quarter; patent window dressing comes at the expense of lower quality. The higher than usual patent applications in the 4th quarter, coupled with a significant drop in patent quality, are consistent with a window dressing explanation.

Second, I exploit a quasi-natural experiment that has exogenously increased the costs of window dressing. Before March 2013, the strategy of postponing patent filing was a low risk one. Under the "first to invent" legal principle, the patent was granted to the firm that could show it was the first to conceive and develop a prototype, and not to the firm that was the first to file the patent application. In 2013 the US patent system switched over to a First to File system following Leahy–Smith America Invents Act (AIA for short), so that in the case of multiple applications of the same innovation the patent was granted to the entity that has filed the application first. This legal change has increased the costs of window dressing for two reasons. When firms try to file for patent applications that are not ready, the chances of rejection are high. The time gap between which a firm is informed of patent rejection and when it revises the patent application for the next filing gives rivals an opportunity to file for the same patent application and exploit "first to file" status. This in turn, induces a huge cost on firms that apply for a patent that is not fully ready. Consequently, AIA implementation offers a quasi-natural experiment to test whether the clustering of patent applications in the 4th quarter is a deliberate attempt on the part of firms to window dress their innovation portfolio. I find that post-AIA there has been a decrease in patent applications in the last quarter. I also find that the quality of last quarter patents has improved.

Another possible explanation of the observed results might be based on motivation. First, inventors at the firm might be motivated to end their fiscal year on a positive note. This might be driven by deadlines, bonuses, etc. I call this the fiscal year hypothesis. Second, firms might try to show a rosy picture of its innovation portfolio before the calendar year-end. This leads to higher stock valuation for the firm and gives their institutional shareholders better performance at the end of a calendar year which is when many investors evaluate their portfolios. I call this the calendar year hypothesis. There is an important distinction here between the two hypotheses. The former is driven by an individual's decision while the latter is driven by the firm's decision-making process. Furthermore, these are not competing hypotheses. An inventor can finish off the tasks at hand in the final quarter, yet the firm ultimately decides when the patent application will be filed through their internal or external legal team. The key feature of these two different hypotheses is to show which one ultimately matters in the final application process. I look at the public firms with fiscal year-end in December and those other than December. My results show only a weak presence of patent window dressing for firms with non-December year end; the effect is much weaker compared to firms with December year-end. It indicates that firms are more likely driven by a desire to show an improved picture of their performance and hence they are window dressing.

Next, I ask what types of firms engage in window dressing their innovation. If patent application clustering is truly a window dressing behavior, I should see that the extent of this behavior is negatively affected by external monitoring and positively by information asymmetry (Degeorge et al., 1999). One of the key players monitoring firms and generating information are analysts. Irani and Oesch (2016) show that reduction in analyst coverage leads to lower quality of financial reporting and higher usage of discretionary earnings. Building upon prior literature, I hypothesize that if firms actively manipulate patent filings, stronger external monitoring should reduce this behavior. Indeed, I find that there is a reduction in the 4th quarter patent applications when more analysts track the firm. Using the number of analysts that follow a firm as a source of external monitoring and a rich set of firm level control variables, I see that firms reduce their patent clustering during their last fiscal quarter significantly when they are followed by more analysts.

Finally, I look at another powerful external monitor - Institutional investors, who are more sophisticated than retail investors and monitor firms more extensively. Specific to my question, existing evidence demonstrates that institutional ownership is associated with higher-quality reporting, as evident in better earnings quality (Velury and Jenkins, 2006) and lower fraud probabilities (Sharma, 2004; Chen et al., 2006). Following the literature, I hypothesize that there is a negative correlation between firm institutional ownership and patent clustering in the 4th quarter. I construct my independent variable as the sum of all shares owned by institutions divided by the overall shares of a firm to capture the intensity of institutional ownership. I find that institutional investment reduces patent clustering in the fourth quarter.

This chapter adds to several strands of literature. First, I identify another dimension of window dressing. Several papers show that fund managers manipulate and alter their portfolios to attract more investors by selling losing shares and buying winning stocks at the end of each reporting period (Lakonishok et al., 1991). This is common across different fund types and asset classes (He, Ng and Wang, 2004; Morey and O'Neal, 2006). Window dressing, however, is not limited to funds. Firms can also window dress by real earnings management through manipulating R&D (Baber et al., 1991; Dechow and Sloan, 1991). Burgstahler and Dichev (1997) and Degeorge, et.al (1999) show that firms actively manage their earnings to pass certain thresholds. Overall, these papers show that window dressing is practiced at the firm level to manipulate investor sentiment. Although previous papers have identified firm managers' patterns of earnings management and its relationship with other firm related factors, little has been done with respect to market manipulation through patent filing. Second, I add to innovation literature by identifying firms' pattern of timing the market through patent filing. As such the patent generating process is not random and in this chapter, I show that patent filling is also a function of market considerations.

The rest of the chapter is as follows: in section 2, I describe my data and variables. In section 3, I explain my empirical methodology. After that, I present my findings in section 4. In section 5, I list my robustness methods and results. Finally, I conclude the chapter in section 6.

2 Data and descriptive statistics

My sample is based on the publicly available patents data from USPTO and spans the period of 1976 – 2020. USPTO's PatentsView project provides data on all granted patents including the applications' filing date. I use this data to compute the measures of patent quality. My first measure is the adjusted citation counts received by the patent. To mitigate the problem of citation truncation I follow the fixed-effect procedure by Hall, Jaffe and Trajtenberg, 2001. My other measure of patent quality is an indicator variable for breakthrough innovation (Byun, et. al 2020). I identify a patent as a breakthrough, or Top 10 patent, if the citations received by that patent is in the top 10% of all citations received by all patents in that year. By focusing on these measures, I can identify patents which allow more future innovation and hence have a higher technological value. The citation distribution is corrected using the fixed effect approach as before. There are still possible truncation issues within a year. This means that patents that are applied for in first months of a calendar year have more time to get cited compared to the patents filed during the last months of the same year. To address this issue, I use a modified year-quarter fixed effect approach as well where I deflate the citation by the year-quarter average. The results are not materially different.

I use the dataset available from Kogan, Papanikolaou, Seru and Stoffman (2017) (hereafter KPSS) to match patents with their public firm owners. KPSS employs a disambiguation algorithm to find PERMNO of each public patent owner using the name of the patent owners and matching them with the names of the firms in CRSP. Using PERMNO_GVKEY link, I can then match my patent dataset with Compustat firms and get the firm level accounting performance data, as well as the fiscal year-ends. After matching the KPSS data with USPTO, I are left with 1,676,630 patents for which I have identified a firm. I next aggregate the patent data at the firm level. I end up with 92,764 year-quarter observations for firms. I list the summary statistics at patent level and aggregate firm level in table 1 Panels A and B, respectively.

Table 1

On average, each firm in my sample applies for 15.206 patents in each quarter with a median value of 3 patents. Patents in my sample receive on average 11 citations. Similarly, firms have on average 2.3 Top 10 patents. That indicates that about 15.1% (2.296/15.206) of patents applied by public firms during that period are breakthrough innovation based on the Top 10 measure. I also calculate the innovation intensity for a given firm in each fiscal quarter by calculating the fraction of patents applied as follows:

$$Total\ Fraction = \frac{Total\ Patents\ applied\ for\ in\ the\ Fiscal\ Quarter}{Total\ Patents\ applied\ for\ in\ the\ Fiscal\ Year} \quad (1)$$

Summary statistics for $Total\ Fraction$ indicate that around 40% of all patents are filed during the 4th quarter. The fact that this value deviates so much from 25% indicates that patents are not distributed equally across quarters. To calculate the innovation quality, I calculate similar fractions for the breakthrough measures as follows:

$$Top\ 10\ Fraction = \frac{Total\ Top\ 10\ Patents\ in\ the\ Fiscal\ Quarter}{Total\ Patents\ applied\ for\ in\ the\ Fiscal\ Quarter} \quad (2)$$

To study the motivations behind the window dressing effect, I make use of data on analysts and institutional ownership. First, I use IBES analyst data to study how many analysts follow firm *i* at each particular time t (Harris and Marston, 1992; Frnakel, Kothari and Weber, 2006; Mohanram et al., 2020). Second, I also use Thomson Reuters' institutional investor 13F data to examine the fraction of institutional ownership for each firm.

3 Empirical methodology

To study the patent application pattern, I start with the individual granted patents in my sample. To establish the patent clustering phenomenon econometrically, I aggregate the total patents applied for in each quarter and run a regression on quarter dummies with the following specification:

$$Total\ Patents_q = \alpha + \sum_{k=2,3,4} \beta_k \times QtrDummy_{k,q} + \varepsilon_q \quad (3)$$

Here q represents the year-quarter observation based on calendar quarter. $Total\ Patents_q$ are the total patents applied for in the given quarter, q. $QtrDummy_{k,q}$ represents the k^{th} quarter dummy (k = 2, 3 & 4) for the q^{th} quarterly observation and is equal to 1 if the given q^{th} quarter observation is the k^{th} calendar quarter. β_k represents the coefficient of the quarter dummy. I add the application year fixed effect to address the concern that the overall number of patents produced has been gradually increasing over time.

Next, I analyze the quality of these patents by looking at the adjusted citations received by the patent. Since the adjusted citation measure is available at the patent level, I don't aggregate the citations and can run the following regression:

$$Adjusted\ Citations_i = \alpha + \sum_{k=2,3,4} \beta_k \times QtrDummy_{k,i} + \varepsilon_i \quad (4)$$

Here *i* represents the i^{th} patent. $QtrDummy_{k,i}$ represents the k^{th} quarter dummy (k = 2, 3 & 4) for the i^{th} patent and is equal to 1 if the given patent was applied for in the k^{th} calendar quarter. β_k represents the coefficient of the quarter dummy. Application year fixed-effect is included to control for year-to-year differences in patent quality. As there can be fundamental time-invariant differences in the firms applying for these patents, I include the Firm fixed-effect and cluster the standard errors at the firm level.

To further highlight that these patents are truly different in quality, I look at an alternate measure of quality, the *Top 10* indicator variable. *Top 10* is equal to 1 for a given patent, if the patent has received enough citations to be in the top 10 percentile of all patent citations applied for in the given year. These measures allow me to discern the relative quality of the patents being applied for. I run a logistic regression for these measures, specified as follows:

$$Top\ 10\ dummy_i = \alpha + \sum_{k=2,3,4} \beta_k \times QtrDummy_{k,i} + \varepsilon_i \quad (5)$$

As before, i refers to the ith patent. $QtrDummy_{k,i}$ represents the k^{th} quarter dummy (k = 2, 3 & 4) for the i^{th} patent and is equal to 1 if the given patent was applied for in the k^{th} calendar quarter. β_k represents the coefficient of the quarter dummy.

To study the firm's behavior, I aggregate the patent level measures at the firm level. Importantly, I now change the definition of a quarter from calendar year to that of fiscal year for a firm. That is because different firms have different fiscal year-ends. By looking at the quarterly data based on a given firm's fiscal year-end, I can separate the calendar year and fiscal year effects. I look at the relative distribution of patent applications of a firm in a given fiscal year by using the following regression:

$$Total\ Fraction_{i,q} = \alpha + \sum_{k=2,3,4} \beta_k \times QtrDummy_{k,i,q} + Controls_{i,q-1} + \varepsilon_{i,q} \quad (6)$$

Here i refers to the i^{th} firm. q is the q^{th} fiscal quarter observation for the firm. $Total\ Fraction_{i,q}$ is the sum of patents applied for by a firm in a given fiscal quarter scaled by the sum of all patents applied for by the firm in the same fiscal year. $QtrDummy_{k,i,q}$ represents the k^{th} quarter dummy (k = 2, 3 & 4) for the i^{th} firm and is equal to 1 if the given firm quarter observation is the k^{th} fiscal quarter. β_k represents the coefficient of the quarter dummy. $Controls_{i,q-1}$ are the set of standard control variables for the i^{th} firm for the q-1th fiscal quarter observation. I define similar regression models for the patent quality measures.

To understand this phenomenon more and identify possible channels, I look at several factors. Specifically, I study how patent clustering during fourth quarter is affected by vigilante external monitoring, namely institutional shareholders, and analysts' coverage. The regression below represents my approach.

$$4Qtr\ Fraction_{i,t} = \beta_1 \times Analyst_{i,t-1} + Controls_{i,t-1} + \alpha_i + \alpha_{j,t} + \varepsilon_{i,t} \quad (7)$$

I define *4Qtr Fraction* as the number of patents applied in the last fiscal quarter of each fiscal year t divided by the number of patents filed during that fiscal year. $Analyst_{i,t-1}$is the number of analysts that follow firm i in fiscal year t-1. I augment my regressions by adding firm and industry year fixed effects. I also use firm level control variables lagged one year. The definition of control variables are in the Appendix. I also try other specifications by replacing industry-year fixed effects with year fixed effects and/or removing control variables.

I follow the same procedure to study the effect of institutional ownership on patent clustering.

$$4Qtr\ Fraction_{i,t} = \beta_1 \times Institute_{i,t-1} + Controls_{i,t-1} + \alpha_i + \alpha_{j,t} + \varepsilon_{i,t} \quad (8)$$

The specification description remains the same as the model before with the exception that the main dependent variable has changed. $Institute_{i,t-1}$, my main independent variable is the number of shares institutional shareholders hold scaled by the overall number of shares both calculated at the end of fiscal year t-1.

4 Empirical findings

The signs of patent clustering are first evident when I look at the individual patent application behavior. Table 2 shows the results at the patent level.

Table 2

Column 1 shows the results of quarterly patent applications regressed on the quarter dummies, adjusted for application year fixed effect for the 179 quarters in my sample period. By controlling for the application year, I remove the year-to-year changes in application behavior as well as demean the observations by the quarterly average over the calendar year. I see that for the 4^{th} quarter, there are on average 894 more patent applications over the 1^{st} quarter which is both larger than any other quarter coefficient and statistically significant. The next largest quarter is the 2^{nd} quarter with 580 more patent applications over the 1^{st} quarter. The 1^{st} and 3^{rd} quarter are not statistically different. Thus, the 4^{th} quarter establishes itself as the dominant quarter for patent applications being almost ~55% (894/580) larger than the next highest quarter.

Next, I look at the quality of these patents. Column 2 shows the citations received by an individual patent adjusted for truncation lag. I find that the increased patenting activity is associated with a significant drop in quality. 4^{th} quarter patents received 0.1159 fewer citations than patents in the 1^{st} quarter. The 2^{nd} and 3^{rd} quarters experienced similar drops in citations received but, the drop was largest for the 4^{th} quarter being almost ~54% (-0.1159/-0.075) larger than the next largest drop in citations which was for the 3^{rd} quarter. As the patents in my sample represent those which were identified to a firm, I also repeat the regression with controls for firm fixed effect and cluster the standard errors at the firm level. This helps me control for any firm specific characteristics which might be driving these results. I also add the application year fixed effect. The results are in column 3, which are nearly identical in nature. The 4th quarter still has the largest drop in citations being almost ~44% (-0.1393/-0.0969) larger than the next largest drop.

I repeat the same steps for my other 2 measures of patent quality, namely Top 10 patent dummies. The results of the logistic regressions further cement the trend I saw earlier. The probability for a patent to be a top 10 patent is negatively affected the most for the 4th quarter being approximately 14.4%. The next lowest quarter is the 3rd quarter with a probability of 16.1%. That is a 1.7% drop in probability in moving from the 3rd to the 4th quarter. Hence, I see that firm patents were disproportionately applied for in the last quarter with more applications in the last quarter and an associated drop in patent quality.

I next analyze firm level measures to see if the pattern continues at the firm level. I aggregate these patents measures at the firm level and analyze if these trends continue. The result of this analysis is presented in table 3.

Table 3

Column 1 shows the fraction of patent applications, regressed on the quarter dummies based on fiscal year ends. I see that the 4th fiscal quarter patent application fraction is larger and statistically significant with a value of 0.4051, a 2.3% (0.009/0.3961) increase over the average quarter value. This means that for firms with 4th quarter patent applications in a fiscal year (23,190 fiscal quarter observations in my sample), the 4th quarter patents represent over 40% of the yearly applications on average when present for the firm. The 2nd quarter patent application is statistically not different from the 1st quarter, while there is a drop in the fraction value for the 3rd quarter. The 4th quarter effect is present even when I control for firm and fiscal year fixed effects. The results are in column 2, which show that the 4th quarter coefficient is positive and statistically significant with a value of 0.0085.

The other columns in the table show the quality of these patent applications in the respective quarters. The average adjusted citations received by the patents in each quarter for the firm is given in column 3. I see that unlike quarter 1, 2 and 3, there is a significant drop in the citations received by the 4th quarter patents. The coefficient for the 4th quarter is negative and statistically significant with a value of -0.0602. This represents a 5% (0.0602/1.2525) reduction in citations received on average by patents filed by firms in the 4th quarter. Even when I control for firm fixed effects and fiscal year fixed effects, column 4, the 4th quarter coefficient is negative, statistically significant, and more than twice as large as the next coefficient showing a significant drop in citations received by 4th quarter patent applications.

A similar story plays out when I look at the measure of breakthrough innovation at the firm level. Column 5 shows that on average considerably lower number of patents applied for by a firm in the 4th quarter end up being a top 10 patent, that is almost 7.9% (0.0164/0.2088) lower than the average value. Controlling for firm and fiscal year fixed effect does not remove this trend, with a negative coefficient value of -0.006 which is statistically significant for the 4th quarter.

I now turn my focus onto the external factors which contribute to the different levels of patent window dressing among firms. Given that I see firms have a large negative relation between high patent filing in the last quarter and the quality of the patents, I hypothesize that increased external monitoring should have an adverse impact on the intensity of this patent clustering phenomenon. I first look at analyst coverage that firms receive as a source of external monitoring. As the number of analysts that follow a firm increase, the fraction of patents applied by the firm in the last quarter should decrease. I test this hypothesis in a regression setting and the results are presented in table 4.

Table 4

From column 1, I see that there is a strong negative relationship between the number of analysts that follow a firm and the fraction of the patents applied by the firm in the 4th quarter. The coefficient for the independent variable *Analysts* is -0.006. The average firm in my sample has about 4.64 analysts following the firm, which means there is a drop of 0.0278 (4.64 x 0.006) in the fraction of applied patents in the 4th quarter. I run the same regression with different specifications for fixed effects. The results are shown in columns 2, 3 and 4. The coefficient for the number of analysts remains negative and statistically significant. Thus, I see that with increased external monitoring, firms tend to reduce their 4th quarter applications.

I follow a similar strategy to see if internal monitoring has the same perceived effect on patent clustering as external monitoring. To this effect, I use the number of institutional shareholders as a proxy for the level of internal monitoring. The results are presented in table 5.

Table 5

From column 1, I see that there is a strong negative effect of institutional ownership on patent clustering by firms. The coefficient for the independent variable *Institute*, which is the number of shares held by institutional shareholders scaled by the total common shares outstanding, is negative at -0.103 and statistically significant. The average firm in my sample has an institutional shareholding of 0.48. That translates to a drop in 4th quarter patent application fraction of 0.049. I run the same regression with different specifications for fixed effects. The results are shown in columns 2, 3 and 4. The coefficient for the institutional ownership variable remains negative and statistically significant. Thus, I see that with increased investor monitoring, firms tend to reduce their 4^{th} quarter applications.

5 Robustness tests

In the previous section, we saw that patent applications in the last quarter represents a major proportion of the overall patent applications for firms and these patents have lower citations received and are less likely to be breakthrough innovations. Here, I intend to see whether window dressing exists for firms with non-December fiscal year-end. To check this, I use a sub-sample of my firms which have non-December fiscal year end. The results are presented in table 6.

Table 6

From column 1, I see that for firms with fiscal years not ending in December, the 4^{th} quarter is no longer significantly different from the 1^{st} quarter. The 4^{th} quarter fractional patent application turns out to 0.4168 which is higher than the value for all firms, 0.4051. The 2^{nd} and 3^{rd} quarters receive lower patent applications overall. Column 2 shows that when I control for firm and fiscal year fixed effects the 4^{th} quarter is positive and slightly statistically significant. The coefficient for the 4^{th} quarter is 0.0062, compared to 0.0085 for all firms. Columns 3-8 represent my analysis of patent quality. Columns 3 and 4 show that the average quality of the patents based on citations is not significantly different among the 4 quarters. Column 5 shows the same result for top 10 breakthrough patents with not significant differences between the quarters. There is an increase in

Top 10 patents when I account for firm and fiscal year fixed effects, from column 6, for quarters 3 and 4. So, with these set of results I can attribute the patent clustering phenomenon mostly to the calendar year effect. That suggests that firms strategically time patent applications when investors need better performance from them.

The window dressing hypothesis assumes that there are minimal costs associated with timing patent applications. If costs of window dressing increase, managers might stop doing window dressing. To check the existence of costs in patent window dressing, I make use of a quasi-natural experiment. In March 2013, the America Invents Act (AIA) came into full effect. With the switch from first-to-invent to first-to-file system, firms now faced a costly choice whether to time their patents. If prior to AIA, firms strategically delayed their lower quality patents to wait until the year-end to pad their innovation portfolio, after AIA I expect the last quarter to no longer have the same fraction of patent applications. To test this out, I use the following model specification:

$$Total\ Fraction_{i,q} = AIA_q + \sum_{k=2,3,4} \beta_k \times QtrDummy_{k,i,q} + \sum_{l=2,3,4} \gamma_l \times AIA_q \times QtrDummy_{l,i,q} + Controls_{i,q-1} + \varepsilon_{i,q} \quad (9)$$

Here i refers to the i^{th} firm. q is the q^{th} fiscal quarter observation for the firm. $Total\ Fraction_{i,q}$ is the sum of patents applied for by a firm in a given fiscal quarter scaled by the sum of all patents applied for by the firm in the same fiscal year. AIA_q is a dummy variable which is equal to 1 if the current quarter is after March 2013. $QtrDummy_{k,i,q}$ represents the k^{th} quarter dummy (k = 2, 3 & 4) for the i^{th} firm and is equal to 1 if the given firm quarter observation is the k^{th} fiscal quarter. β_k represents the coefficient of the quarter dummy. γ_l is the coefficient for the interaction term between the AIA dummy and the l^{th} quarter dummy. $Controls_{i,q-1}$ are the set of standard control variables for the i^{th} firm for the $q\text{-}1^{th}$ fiscal quarter observation. I define similar regression models for the patent quality measures. The results for these regressions are presented in table 7.

Table 7

Column 1 shows the pre and post AIA fractional patent applications for the quarters. I find pre-AIA the 4^{th} quarter had 0.416 (0.395 + 0.021) of all patent applications, whereas post-AIA this fractional amount drops to 0.344 (0.395+0.021-0.076+0.004). This represents a 17.31% (|0.416-0.344|/0.416) drop. This clearly shows that once the cost of timing patent applications is introduced to managers objective function, they can no longer inflate applications during the fourth quarter. Column 2 shows that pre-AIA the 4^{th} quarter contributed 0.0190 towards the fractional patent applications, while post-AIA this went down to -0.0546. Next, I look at the quality of these patents. Before moving on to the quality measures, one point needs further discussion. Looking at the co-efficient of the interaction terms of quarters 2, 3 and 4 from column 1, one can find that they are all significant and negative. This might seem to suggest that after the adoption of AIA managers started targeting the first quarter and this would not be in line with a window dressing argument. However, this result is expected and is explained as follows. With managers engaging in window dressing, they would likely try to stockpile a set of patents that they could use at the end of the year, and this would likely start in the first quarter. When AIA came into effect, managers could no longer wait around, and this is why we see the drop across all quarters, a sort of regression to the mean. However, this does not mean that the first quarter became the new preferred window dressing quarter. For this to be the case the AIA term needed to be positive and significant, which along with the constant term captures the behavior for the first quarter. From column 3 I can see that pre-AIA 4^{th} quarter patents received on average 1.2749 citations, while post-AIA this value is

0.7739. However, it is difficult to say clearly that this trend is purely a quarter effect as one possible reason can be that the fixed effect approach to citation adjustment hasn't completely corrected for truncation lag. This was not an issue in the earlier regressions as I wasn't comparing two sub-samples directly, as I do here with the pre and post AIA periods. Hence, I must couple the citation result with other measures of quality. That is exactly what I do with the top 10 breakthrough measure. Column 5 shows that pre-AIA 0.1614 or about 16.14% of patents filed in the 4^{th} quarter make it to the top 10 percentile of citations received in a year, whereas post-AIA 0.3454 or about 34.45% of patents are top 10 patents. This shows a reverse trend where the application in the 4^{th} quarter is going down post-AIA while the quality goes up. As such I can conclude that firms have strategically applied for patents towards the end of the calendar year in a bid to window-dress their intellectual capital and future potential when they had the opportunity of making this choice with lower costs.

6 Conclusions

In this chapter I show the window dressing effect in the innovation context for firms. I first look at the overall patent filings for firms and show that there is an increase in patents applications in the last quarter of the calendar year. This increase in patents is accompanied by a drop in patent quality. The last quarter patents receive fewer citations and are less likely to be breakthrough innovations. I also study the patent portfolio at the firm level. Again, I find that firms make patent applications in the last quarter which represents a large portion of their yearly patent applications. This ties in with my previous observation of more patents being filed in the last quarter. On average 4^{th} quarter patents represent almost 40% of the total yearly patent filings. However, the quality of these patents deviates from the patents filed in other quarters. These last quarter patents receive fewer citations and are less frequently breakthrough patents.

I provide further evidence that this behavior is linked to window dressing on the part of firms by examining the effect of increased monitoring. When there is more monitoring proxied by higher presence of institutional shareholders there is a drop in the fraction of patents applied for in the 4th quarter. A similar result holds when I look at increased external monitoring as proxied by the number of analysts following the firm. This behavior suggests firms may be exploiting the information asymmetry to appear more innovative than they are.

Finally, I provide robustness tests to show that the window dressing behavior is indeed present. First, I look at firms with non-December fiscal year ends and check whether they show a similar behavior. I do not find any evidence that these firms have the same higher 4th quarter patent filings with an associated drop in quality. I find the opposite result with higher patent quality for the last quarter. Next, I look at the patent application behavior in a quasi-natural experiment setting. Specifically, I take the adoption of the America Invents Act (AIA) in March 2013 as an external shock which increases the costs of holding out on patents for strategic timing benefits. I find that post AIA firms see a decrease in the 4th quarter patent filings and an increase in the quality of these patents overall. This strongly suggests that patent applications were not a random phenomenon. Instead, there had been a strategic aspect to when to file a given patent.

My findings add to the current literature by showing an additional dimension to window dressing by firms. Firms exploit information asymmetry and pass off being more innovative, with a larger intellectual asset base than they truly have. They try to pass off more quantity as a substitute for quality right when more eyes are on them. Investors and other stakeholders should consider the possibility of window dressing by firms in the innovation context and integrate this possibility when making decisions accordingly.

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8 Tables

Table 1

Descriptive Statistics

This table reports summary statistics of measures for all granted patents at the patent and firm level respectively. Panel 1A summarizes the characteristics of patents granted from 1976-2020. *Citations* is the total number of citations received by a patent. *Adjusted Citations* is the citation count adjusted for truncation lag using the fixed-effect approach. *Top 10* is a dummy variable which is 1 if the patent is above the 90th percentile of citation distribution of all applied patents in the year. Panel 1B lists summary stats for public and innovative firms with at least one patent granted from 1976-2020. *Average Citations* is the average of adjusted citations received by all patents applied for by the firm in each quarter. *Total Patents* is the count of all patents applied in each quarter. *Top 10 Patents* is the count of patents that are in the 90th percentile of citation distribution of all applied patents in the application year. *AIA Dummy* is a dummy variable which is 1 for firm quarters after March 2013. All firm level variables are observed quarterly with quarters defined by the fiscal year. Panel 1C lists summary stats for public and innovative firms with at least one patent granted from 1976-2020. *4thQtr Fraction* is the fraction of applied patents applied by a firm in the last quarter of a fiscal year scaled by the number of all applied patents to that firm for that fiscal year. *Analysts* is the number of analysts following a firm during fiscal year t. *Institute* is the number of shares held by institutional shareholders scaled by the overall number of shares both calculated at the end of fiscal year t-1 All firm level variables are observed at fiscal year. Control variable definition is given in the appendix. All continuous variables are winsorized at 1% and 99%.

	Mean	Median	1st Qu.	3rd Qu.	SD	Obs
Panel 1A – Patent Level Variables – Granted Patents						
Citations	11.228	3.000	0.000	11.000	23.510	1,676,630
Adjusted Citations	0.943	0.304	0.000	0.940	1.883	1,676,630
Top 10	0.166	0.000	0.000	0.000	0.372	1,676,630
Panel 1B – Firm Level Variables – Quarterly Level Data						
Average Citations	1.230	0.716	0.322	1.412	1.710	92,997
Total Patents	15.206	3.000	1.000	9.000	42.150	92,997
Top 10 Patents	2.296	0.000	0.000	2.000	6.183	92,997
Interest Burden	0.263	0.174	0.055	0.384	0.275	92,764
Book-To-Market	0.629	0.610	0.396	0.840	0.299	92,764
R&D/Sales	0.465	0.032	0.000	0.138	2.257	92,764
LTDI	0.795	1.000	1.000	1.000	0.404	92,764
Log Sales	5.170	5.208	3.585	6.786	2.365	92,764
Total Fraction	0.396	0.302	0.213	0.500	0.270	92,997
Top 10 Fraction	0.201	0.000	0.000	0.250	0.327	92,997
AIA Dummy	0.167	0.000	0.000	0.000	0.373	92,764
Panel 1C-Firm Level Variables-Annual Level Data						
4Qtr Fraction	0.400	0.325	0.222	0.500	0.270	16,545
Analysts	4.640	3.000	0.000	7.000	5.380	16,545
Institute	0.480	0.547	0.159	0.764	0.320	16,545
Cash	0.260	0.181	0.062	0.400	0.250	13,782
ROA	0.080	0.122	0.053	0.179	0.200	13,749
Leverage	0.180	0.150	0.010	0.285	0.180	13,887
Tobin's Q	2.030	1.719	1.275	2.478	1.050	12,170
Log size	7.470	7.352	5.932	9.023	2.140	13,281
R&D	0.100	0.055	0.017	0.122	0.130	13,955
Capex	0.050	0.036	0.020	0.064	0.040	13,673
PPE	0.200	0.160	0.078	0.284	0.170	13,933

Table 2

Patent Applications and Quality of Patents

This table reports the regression results of *Total Patents*, *Adjusted citations,* and *Top 10* Patents on the calendar quarter that a patent is applied in. Sample period is from 1976-2020. *Total Patents* is the count of all patents applied in each quarter. *Adjusted Citations* is the citation count adjusted for truncation lag using the fixed-effect approach. *Top 10* is a dummy variable which is 1 if the patent is above the 90th percentile of citation distribution of all applied patents in the year. *Qtr2*, *Qtr3* and *Qtr4* are dummy variables which are 1 if the fiscal quarter is the 2nd, 3rd and 4th quarter of the fiscal year respectively. Column 1 observations are at the calendar quarter level while observations for column 2-5 are at the patent level. Columns 4 and 5 are logistic regressions. Numbers in parenthesis are *t*-statistics and ***, ** and * denote 1%, 5% and 10% statistical significance, respectively.

	Dependent variable				
	Total Patents	Adjusted Citations		Top 10	
	(1)	(2)	(3)	(4)	(5)
Qtr2	580.222**	-0.017***	-0.044***	-0.072***	-0.056***
	(2.424)	(-3.999)	(-6.055)	(-12.650)	(-5.477)
Qtr3	363.7333*	-0.075***	-0.097***	-0.175***	-0.128***
	(1.753)	(-17.667)	(-11.631)	(-29.810)	(-13.153)
Qtr4	893.955***	-0.116***	-0.139***	-0.309***	-0.205***
	(3.740)	(-28.055)	(-11.751)	(-52.207)	(-15.179)
Observations	179	1,676,630	1,676,630	1,676,630	1,676,630
Application Year FE	YES	X	YES	X	YES
Firm FE	X	X	YES	X	YES
Clus. SE	X	X	FIRM	X	FIRM
Adjusted R^2	0.975	0.001	0.117		
Log Likelihood				-752463	
Deviance				1504926	1132556

Table 3

Public Firms' Innovation Activity and Quality

This table reports the regression results of firm level patenting activity and quality measures applied for by a firm in the fiscal quarter. Sample period is from 1976-2020. *Total Fraction* is the total patents applied in a quarter scaled by the total patents applied for by the firm in the fiscal year. *Average Citations* is the average of adjusted citations received by all patents applied for by the firm in each quarter. *Top 10 Fraction* is the total patents which are above the 90th percentile of the citation distribution of granted patents in the calendar year, in a quarter scaled by the total patents applied for by the firm in the given quarter. *Qtr2*, *Qtr3* and *Qtr4* are dummy variables which are 1 if the fiscal quarter is the 2nd, 3rd and 4th quarter of the fiscal year respectively. Controls used are *Interest Burden*, *R&D/Sales*, *Book-to-market ratio*, *Long-term Debt Indicator* and *Log Sales*. shares both calculated at the end of fiscal year t-1 All firm level variables are observed at fiscal year. Control variable definition is given in the appendix. Numbers in parenthesis are t-statistics and ***, ** and * denote 1%, 5% and 10% statistical significance, respectively.

	Dependent variable:					
	Total Fraction		Average Citations		Top 10 Fraction	
	(1)	(2)	(3)	(4)	(5)	(6)
Qtr 2	0.001	-0.001	-0.011	-0.035***	-0.004	-0.001
	(0.493)	(-0.594)	(-0.676)	(-2.733)	(-1.163)	(-0.559)
Qtr 3	-0.011***	-0.010***	-0.020	-0.047***	-0.009***	-0.002
	(-4.283)	(-5.324)	(-1.261)	(-3.813)	(-3.006)	(-0.844)
Qtr 4	0.009***	0.009***	-0.060***	-0.098***	-0.016***	-0.006***
	(3.540)	(3.869)	(-3.816)	(-7.987)	(-5.428)	(-2.620)
Observations	92,997	92,659	92,997	92,659	92,997	92,659
Controls	X	YES	X	YES	X	YES
Fiscal Year FE	X	YES	X	YES	X	YES
Firm FE	X	YES	X	YES	X	YES
Clus. SE	X	FIRM	X	FIRM	X	FIRM
Adjusted R^2	0.001	0.437	0.000	0.393	0.000	0.441

Table 4

Analyst Coverage and Patent Window Dressing

This table reports the regression results of the effect of the number of analysts on the 4th quarter patent application as a fraction of total patent applications in a fiscal year. Sample period is from 1976-2015. *4Qtr Fraction* is the number of applied patents in the fourth quarter divided by the number of patents applied for throughout the fiscal year. *Analysts* is the number of analysts that follow firm *i* in year *t* and is constructed using IBES analysts' data. Controls used are *Cash*, *ROA*, *Leverage*, *Tobin's Q*, *Log Size*, *R&D*, *Capex* and *PPE*. Control variable definition is given in the appendix. Standard errors are clustered at the firm level. Numbers in parenthesis are standard errors and ***, ** and * denote 1%, 5% and 10% statistical significance, respectively.

	Dependent variable:			
	4Qtr Fraction			
	(1)	(2)	(3)	(4)
Analysts	-0.006***	-0.006***	-0.005***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	16,537	16,545	12,011	12,007
Controls	X	YES	X	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	X	YES	X
Ind x Year FE	X	YES	X	YES
Adjusted R^2	0.372	0.361	0.374	0.378

Table 5

Institutional Shareholders and Patent Window Dressing

This table reports the regression results of the effect of the number of institutional shareholders on the 4th quarter patent application as a fraction of total patent applications in a fiscal year. Sample period is from 1976-2015. The dependent variable *4Qtr Fraction* is the number of applied patents in the fourth quarter divided by the number of applied patents applied for throughout the fiscal year. The variable *Institute* is the number of shares held by institutional shareholders scaled by the overall number of shares both calculated at the end of fiscal year t-1. Control variables are *Cash*, *ROA*, *Leverage*, *Tobin's Q*, *Log Size*, *R&D*, *Capex* and *PPE*. Control variable definition is given in the appendix. Standard errors are clustered at the firm level. Numbers in parenthesis are standard errors and ***, ** and * denote 1%, 5% and 10% statistical significance, respectively.

	Dependent variable:			
	4Qtr Fraction			
	(1)	(2)	(3)	(4)
Institute	-0.103***	-0.105***	-0.027**	-0.021*
	(0.012)	(0.011)	(0.012)	(0.013)
Observations	16,537	16,545	12,011	12,007
Controls	X	YES	X	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	X	YES	X
SIC * Year FE	X	YES	X	YES
Adjusted R^2	0.374	0.362	0.371	0.376

Table 6

Effect of fiscal year endings.

This table reports the regression results of firm level patenting activity and quality measures applied for by a firm in the fiscal quarter for firm with non-December fiscal year ending. Sample period is from 1976-2020. *Total Fraction* is the total patents applied in a quarter scaled by the total patents applied for by the firm in the fiscal year. *Average Citations* is the average of adjusted citations received by all patents applied for by the firm in each quarter. *Top 10 Fraction* is the total patents which are above the 90th percentile of the citation distribution of granted patents in the calendar year, in a quarter scaled by the total patents applied for by the firm in the given quarter. *Qtr2*, *Qtr3* and *Qtr4* are indicator variables which are 1 if the fiscal quarter is the 2nd, 3rd and 4th quarter of the fiscal year respectively. Control variables are *Interest Burden*, *R&D/Sales*, *Book-to-market ratio*, *Long-term Debt Indicator* and *Log Sales*. Control variable definition is given in the appendix. Numbers in parenthesis are *t*-statistics and ***, ** and * denote 1%, 5% and 10% statistical significance, respectively.

	Dependent Variable					
	Total Fraction		Average Citations		Top 10 Fraction	
	(1)	(2)	(3)	(4)	(5)	(6)
Qtr 2	-0.012***	-0.011***	0.001	-0.016	-0.000	0.003
	(-2.630)	(-3.069)	(0.025)	(-0.665)	(-0.017)	(0.641)
Qtr 3	-0.014***	-0.012***	0.007	-0.001	0.001	0.008**
	(-3.018)	(-3.376)	(0.247)	(-0.027)	(0.210)	(2.093)
Qtr 4	0.004	0.006*	-0.006	-0.034	0.005	0.013***
	(0.974)	(1.694)	(-0.207)	(-1.609)	(0.864)	(3.119)
Observations	31,149	31,077	31,149	31,077	31,149	31,077
Control	X	YES	X	YES	X	YES
Fiscal Year FE	X	YES	X	YES	X	YES
Firm FE	X	YES	X	YES	X	YES
Clus. SE	X	FIRM	X	FIRM	X	FIRM
Adjusted R^2	0.001	0.441	-0.000	0.337	-0.000	0.378

Table 7

America Invents Act and Corporate Patenting Activity

This table reports the regression results of the effects of the America Invents Act on corporate patenting activity and quality. Sample period is from 1976-2020. *Total Fraction* is the total patents applied in a quarter scaled by the total patents applied for by the firm in the fiscal year. *Average Citations* is the average of adjusted citations received by all patents applied for by the firm in each quarter. *Top 10 Fraction* is the total patents which are above the 90th percentile of the citation distribution of granted patents in the calendar year, in a quarter scaled by the total patents applied for by the firm in the given quarter. *Qtr2*, *Qtr3* and *Qtr4* are dummy variables which are 1 if the fiscal quarter is the 2nd, 3rd and 4th quarter of the fiscal year respectively. *AIA Dummy* is a dummy variable which is 1 for firm quarters after March 2013. Control variables are *Interest Burden*, *R&D/Sales*, *Book-to-market ratio*, *Long-term Debt Indicator* and *Log Sales*. Control variable definition is given in the appendix. Numbers in parenthesis are *t*-statistics and ***, ** and * denote 1%, 5% and 10% statistical significance, respectively.

	Dependent Variable:					
	Total Fraction		Average Citations		Top 10 Fraction	
	(1)	(2)	(3)	(4)	(5)	(6)
AIA * Qtr 2	-0.053***	-0.041***	-0.023	-0.084**	-0.043***	0.008
	(-8.182)	(-8.160)	(-0.519)	(-2.433)	(-4.281)	(1.375)
AIA * Qtr 3	-0.066***	-0.052***	-0.100**	-0.187***	-0.072***	0.004
	(-10.308)	(-10.724)	(-2.250)	(-5.182)	(-7.138)	(0.601)
AIA * Qtr 4	-0.076***	-0.055***	-0.157***	-0.266***	-0.093***	0.002
	(-11.776)	(-10.269)	(-3.702)	(-7.203)	(-9.234)	(0.307)
AIA	0.004	-0.019**	-0.345***	0.002	0.277***	-0.026**
	(0.820)	(-2.003)	(-10.610)	(0.029)	(37.740)	(-2.425)
Qtr 2	0.010***	0.007***	-0.003	-0.019	0.000	-0.002
	(3.591)	(3.111)	(-0.175)	(-1.359)	(0.050)	(-0.827)
Qtr 3	-0.000	-0.000	0.001	-0.013	-0.000	-0.002
	(-0.025)	(-0.170)	(0.060)	(-1.004)	(-0.017)	(-0.766)
Qtr 4	0.021***	0.019***	-0.030*	-0.051***	-0.003	-0.006**
	(7.441)	(7.673)	(-1.762)	(-3.919)	(-1.094)	(-2.327)
Constant	0.395***		1.305***		0.1646***	
	(197.130)		(106.149)		(78.929)	
Observations	92,764	92,657	92,764	92,657	92,764	92,657
Controls	X	YES	X	YES	X	YES
Fiscal Year FE	X	YES	X	YES	X	YES

Firm FE	X	YES	X	YES	X	YES
Clus. SE	X	FIRM	X	FIRM	X	FIRM
Adjusted R^2	0.006	0.438	0.009	0.393	0.067	0.441

9 Appendix

9.1 List of variables and definitions

Name	Definition
Adjusted Citations	This is the citation count adjusted for truncation lag using the fixed-effect approach as per Hall, Jaffe and Trajtenberg (2005).
Top 10 Dummy	This is a dummy variable which is 1 if the patent is above the 90^{th} percentile of citation distribution of all granted patents in the year.
Average Citations	This is the average of adjusted citations received by all patents applied for by the firm in each fiscal quarter.
Total Fraction	This is the total patents applied for in a fiscal quarter scaled by the total patents applied for by the firm in the fiscal year.
Top 10 Fraction	This is the sum of all patents which are above the 90^{th} percentile of the citation distribution of granted patents in the calendar year, in a fiscal quarter scaled by the sum of patents applied for by the firm in the same fiscal quarter.
Interest Burden	The three-year average of interest expense scaled by operating income before depreciation.
Book-To-Market	The three-year average ratio of book value of assets over the sum of book value of liabilities and market value of equity.
R&D/Sales	The three-year average of research and development expense scaled by sales.
LTDI	An indicator variable for long-term debt, which is equal to 1 if the firm has long-term debt outstanding and 0 otherwise.
Log Sales	Log of the total sales each fiscal quarter.
AIA Dummy	This is a dummy variable which is 1 for firm fiscal quarters after March 2013.
Firm level variables	
4Qtr Fraction	Fraction of granted patents granted to a firm in the last quarter of a fiscal year scaled by the number of all granted patents to that firm for that fiscal year

Analysts	Number of analysts following a firm during year t
Institute	The number of shares of a firm held by institutional shareholders scaled by the overall number of shares both calculated at the end of fiscal year t-1
Cash	The value of cash holdings over assets both measured at fiscal year-end t-1
ROA	EBITDA over assets both measured at fiscal year-end t-1
Leverage	Long-term debt over assets both measured at fiscal year-end t-1
Tobin's Q	(Book value of assets - common equity + market value of equity - deferred taxes and investment tax) divided by (book value of assets -0.1 * common equity + 0.1 * market value of equity)
Log size	Natural log of one plus the market value of firm both measured at fiscal year-end t-1
R&D	Research and development over assets both measured at fiscal year-end t-1
Capex	Capital expenditures scaled by assets both measured at fiscal year-end t-1
PPE	Property plant and equipment scaled by assets both measured at fiscal year-end t-1

Conclusion

In the first 2 chapters of this dissertation, I have looked at the use of rank-and-file employee option grants (RFO) and their use by firms. In chapter 1, I discuss the use of RFO as a retention tool by firms that are involved in corporate innovation. I presented evidence to show that not all employees are treated equally and firms that have invested more into innovation and have a larger base of innovation assets are the ones that issue more RFO. This in turn suggests that the key motive behind using RFOs as a retention tool is the retention of inventors at the firm.

In chapter 2, I build on the insights of chapter 1 and study how effective are RFOs at retention. Given their use by firms with more R&D, I look at inventors and their employment history. I find that unlike the case for general employees, RFOs have a positive and permanent effect at retaining inventors. This result reinforces the use of RFOs primarily by firms with a large innovation base. The use and effectiveness of RFOs are directed at the subset of employees who are involved in the production of intellectual property for the firm, namely inventors.

In my final chapter, I look at a separate phenomenon tied to corporate innovation which is the application of patents by firms. I show that a large majority of patent applications are made in the last quarter of the calendar year. These patents also suffer from a lower quality. I show that this is mainly a window dressing effect on the part of firms who are actively trying to manipulate investor outlook for themselves by projecting a successful patent portfolio. I also show that this behavior is mitigated when internal and external monitoring of the firm is increased.