

# Non-executive Employee Stock Options and Corporate Innovation

Xin Chang, Kangkang Fu, Angie Low, Wenrui Zhang\*

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## Abstract

We provide empirical evidence on the positive effect of non-executive employee stock options on corporate innovation. The positive effect is more pronounced when employees are more important for innovation, when free-riding among employees is weaker, when options are granted broadly to most employees, when the average expiration period of options is longer, and when employee stock ownership is lower. Taken together, our results are consistent with the view that stock options granted to non-executive employees increase risk-taking incentive, enhance failure-bearing capacity, encourage long-term commitment, and promote teamwork of employees, leading to greater innovation success.

*JEL Classification:* J33, M52, O31

*Keywords:* Employee Stock Options; Corporate Innovation; Risk-taking Incentives; Employee Compensation

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\* Xin Chang, Kangkang Fu, and Angie Low are from the Division of Banking and Finance, Nanyang Business School, Nanyang Technological University, Singapore 639798. Wenrui Zhang is from the Institute for Financial & Accounting Studies, Xiamen University, Xiamen, China 361005 (E-mail: [changxin@ntu.edu.sg](mailto:changxin@ntu.edu.sg), [c090020@e.ntu.edu.sg](mailto:c090020@e.ntu.edu.sg), [aaclow@ntu.edu.sg](mailto:aaclow@ntu.edu.sg), and [wrzhang@xmu.edu.cn](mailto:wrzhang@xmu.edu.cn), respectively). We are grateful for the valuable comments and suggestions from Ilona Babenko, Dong Chen, Po-Hsuan (Paul) Hsu, and seminar participants at EM Lyon Business School, Erasmus University Rotterdam, Nanyang Technological University, University of Stavanger, the 2012 China International Conference in Finance, and the 2013 Midwest Finance Association Annual Meeting. All errors are our own.

*Most great ideas for enhancing corporate growth and profits aren't discovered in the lab late at night, or in the isolation of the executive suite. They come from the people who daily fight the company's battles, who serve the customers, explore new markets and fend off the competition. In other words, the employees.*

*The Wall Street Journal (August 23, 2010) – “Who Has Innovative Ideas? Employees.”*

## **I. Introduction**

Innovation has become an increasingly important corporate strategy that boosts the long-term growth and enhances the competitiveness of a firm. By fostering the innovative streak, *Google*, one of the most innovative companies according to *Business Week*'s annual survey in 2010, has achieved phenomenal success in the last decade, growing from a small firm to a company with market capitalization of approximately \$250 billion as of January 2013. An important part of *Google*'s success lies in its ability to understand and adopt the credo that creativity is nurtured from individual employees. *Google* describes its innovation policy as “*Our commitment to innovation depends on everyone being comfortable sharing ideas and opinions. Every employee is a hands-on contributor, and everyone wears several hats. Because we believe that each Googler is an equally important part of our success...*”. In the meantime, according to the *New York Times* (November 12, 2007), *Google*'s current and former employees collectively hold vested stock options that were worth roughly \$2.1 billion as of November 2007.

Is the extensive use of employee stock options a key driving force behind the innovation success of companies such as *Google*? In this paper, we answer this question by examining the incentive effect of non-executive employee stock options on corporate innovation.<sup>1</sup>

Innovation is about people. Innovation arises when active, motivated, and engaged people generate ideas and convert them into new products, services, or business models. Holmstrom

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<sup>1</sup> Companies widely recognize the positive effect of employee stock options on corporate innovation. For instance, Cisco Systems, Inc., the world leader in communication and information technology, stated in its high tech policy guide (January 2005) that “*Employee stock options fuel innovation and the entrepreneurial spirit.*”

(1989) points out that corporate innovation, unlike conventional investments in tangible assets, involves a high probability of failure due to its dependence on various unpredictable conditions. As a result, the standard incentive schemes based on the pay-for-performance principle are insufficient in encouraging innovations. Instead, the model of Manso (2011) and the experimental study of Ederer and Manso (2012) show that managerial incentives that tolerate early failure and reward long-term success lead to better innovation performance. Several empirical studies examine managerial incentives and institutional factors that influence innovations, and document results generally consistent with these arguments.<sup>2</sup>

Although the abovementioned studies greatly enhance our understanding of the mechanisms that motivate executives (managers) to be more innovative, how non-executive employees and their compensation schemes affect corporate innovation has received little attention so far. This lack of evidence is surprising since most companies, beginning in the late 1980s, have changed the innovation process by replacing centralized corporate research and development (R&D) laboratories with divisional laboratories (Lerner and Wulf 2007), making rank-and-file employees increasingly more important innovators in firms.<sup>3</sup>

We expect non-executive employee stock options to have a positive effect on corporate innovation for four reasons. First, innovation requires risk-taking. Non-executive employee stock options positively relate employee wealth to stock return volatility, incentivizing employees to take more risk in the innovation process. Second, rewards for long-term success and tolerance for early failure are crucial for innovation success (Manso 2011). The asymmetric

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<sup>2</sup> See among others, Lerner and Wulf (2007), Aghion, Van Reenen, and Zingales (2013), Chemmanur and Tian (2011), Tian and Wang (2013), Francis, Hasen, and Sharma (2011), and He and Tian (2013). We review the literature in greater detail in Section II.

<sup>3</sup> Anecdotal evidence in Harden, Kruse, and Blasi (2008) supports the view that non-executive employees are highly important innovators in a firm: “*Whirlpool credits their successful product innovations not to a couple of departments, such as engineering or marketing. Instead, they contribute their success to the 61,000 employees who have the ability to contribute and develop product, service, or processes innovations* (pp. 4).”

payoff structure of stock options not only rewards employees with unlimited upside potential when innovation succeeds and stock prices increase, but also protects them with limited downside loss when innovation fails and stock prices fall. Third, innovation projects are long-term, multi-stage, and labor intensive (Holmstrom 1989). Employee stock options normally have a long vesting period and a long average time to expiration.<sup>4</sup> To exercise their options, employees have to stay with their firms until options become exercisable (Core and Guay 2001). Therefore, the deferral feature of employee stock options can effectively direct employees' attention to the firm's long-term success and encourage employees' long-term human capital investment in innovation (Rajan and Zingales 2000). Finally, innovation takes teamwork. Dougherty (1992) and Van de Ven (1986) show that team-based work increases the quantity and quality of innovation. The laboratory experiment of Ederer (2009) finds that innovation success and performance are greatest when innovators receive a *group* incentive scheme that rewards long-term *joint* success. Non-executive employee stock options, as a group incentive scheme with value determined by employees' joint effort, can enhance cooperation between employees, induce mutual monitoring among co-workers (Baker, Jensen, and Murphy 1988, Hochberg and Lindsey 2010), and encourage information sharing and social learning between innovators, leading to greater innovation success.<sup>5</sup>

Using a large panel of US firms covered by the National Bureau of Economic Research (NBER) Patent and Citation Database, we document that non-executive employee stock options foster corporate innovation. Specifically, we follow Hochberg and Lindsey (2010) and define non-executive employees as all employees except the top five executives in a firm. We estimate

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<sup>4</sup> The vesting period of stock options refers to the amount of time it takes for options to become fully exercisable. The survey of National Center for Employee Ownership (2001) reveals that vesting periods of employee stock options generally range between one and seven years. Four years is the most common.

<sup>5</sup> Henderson and Cockburn (1994) document that the sharing of information and experiences among R&D workers positively affects innovation performance of firms.

the Black-Scholes value of non-executive employee stock options using data retrieved from the Investors Responsibility Research Center (IRRC) Dilution Database and ExecuComp. Our main results are that the value of non-executive stock options per employee has a positive and significant impact on the quantity and quality of innovation output, measured by the number of patents and the number of patent citations, respectively. Although firms with higher value of non-executive employee stock options also make more R&D investment as innovation input, we find that our main results hold after controlling for the increased input into innovation.

Apart from performing a variety of checks to ensure that our main results are robust to alternative model specifications and variable definitions, we design a number of tests to address the problem of omitted variables that are related to firm financial constraints, corporate governance, and industry geographic clustering, all of which could drive both innovation and employee stock options. To account for reverse causality that goes from innovation to employee stock options, we control for several variables that capture innovative firms' incentive to use stock options to sort or retain employees (e.g., Core and Guay 2001, Oyer 2004, Oyer and Schaefer 2005). These additional tests do not affect our main results. To further mitigate endogeneity concerns, we follow Hochberg and Lindsey (2010) and perform two-stage least squares (2SLS) regressions using two instrumental variables, i.e., stock options granted to employees of *non-innovative* firms that are geographically proximate but are from *other* industries and the number of shares outstanding. Our main results still hold, suggesting that the effect of per-employee value of stock options on innovation is robust and causal.

We then partition our sample in several ways to examine how the positive effect of employee options on innovation varies across firms. We find that the effect of employee options are stronger 1) when rank-and-file employees are more important for innovation, i.e., the KLD

employee treatment index or per-employee R&D expenditure is higher, 2) when free-riding problems are less severe among non-executive employees, i.e., the number of employees is smaller or the per-employee growth opportunities are higher, 3) when firms have broad-based (as opposed to targeted) non-executive option plans, which have been shown by previous studies (e.g., Hochberg and Lindsey 2010) to enhance cooperation and mutual monitoring among employees, 4) when the average expiration period of stock options is longer, and 5) when employee stock ownership, which has been shown by Bova et al. (2012) to discourage corporate risk-taking, is lower. These results further support our arguments for the positive effect of employee options on innovation.

Employee stock options can create both performance-based (delta) and risk-taking (vega) incentives for rank-and-file employees. To examine which incentive is more important in driving our results, we compute the employee option delta (the sensitivity of option value to stock price) and vega (the sensitivity of option value to stock volatility) arising from non-executive stock options. Our regression analysis reveals that the positive effect of employee options on innovation is driven by option vega rather than delta, confirming the importance of risk-taking in motivating innovation.

Our paper contributes to the extant literature in two ways. First, while previous studies mainly emphasize the role of executives and the importance of managerial incentives in innovation, our work focuses on non-executive employees who have become increasingly important innovators since 1980s. To the best of our knowledge, we are among the first to show how rank-and-file employees and their compensation influence corporate innovation using a large scale analysis. Our results shed light on the positive role of employees, as important stakeholders, in firm value creation via innovation. Second, our findings offer a new explanation

for the theoretically puzzling occurrence of broad-based stock option plans in corporate America (Kedia and Rajgopal 2009). We demonstrate that an important function of broad-based option plans is to foster innovation. By doing so, our analysis also discovers a specific channel through which non-executive stock options affect firm performance, and hence complements the findings of Hochberg and Lindsey (2010) who show a causal and positive impact of broad-based option programs on firm performance.

The remainder of the paper proceeds as follows. Section II provides additional discussion of the literature and hypotheses. We discuss our sample and variables in Section III. We present our main empirical results in Section IV and report additional results in Section V. Section VI concludes.

## **II. Related Literature**

By examining the impact of non-executive employee options on corporate innovation, we bring together two different strands of literature.

First, our paper contributes to the literature on corporate innovation. Motivated by Holmstrom (1989) and Manso (2011), empirical studies have identified various factors that affect managerial incentives for innovation. For instance, Tian and Wang (2013) document that IPO firms backed by more failure-tolerant venture capitalists exhibit higher innovation productivity. He and Tian (2013) document that analyst coverage has a negative impact on innovation because analysts exert too much pressure on managers to meet short-term goals. Aghion, Van Reenen, and Zingales (2013) find that higher institutional ownership ensures CEOs a secure job and hence helps overcome CEOs' myopia and promotes innovation productivity. Chang et al. (2013) show that conservative accounting, which fosters the early recognition of

losses, reduces the tolerance for early failures and impedes innovation. Chemmanur and Tian (2011) document that firm-level anti-takeover provisions protect managers against short-term pressures from the corporate control market, encouraging them to focus on long-term value-enhancing innovative activities. However, Atanassov (2012) uses the enactments of state-level anti-takeover laws to show that hostile takeovers monitor and discipline top managers, leading to better innovation outcomes. Fan and White (2003) and Armour and Cumming (2008) show that ‘forgiving’ personal bankruptcy laws encourage entrepreneurship and innovation. Francis, Hasan, and Sharma (2011) show that golden parachutes and stock options of executives enhance innovation. Hirshleifer, Low, and Teoh (2012) find that overconfident CEO can better exploit innovative growth opportunities and generate greater innovation success.

We focus on the role of rank-and-file employees in innovation, which is still an under-explored topic in the literature. By doing so, our study complements Acharya, Baghai, and Subramanian (2009, 2013) who find that stringent labor laws and wrongful discharge laws that do not punish employees for short-term failures foster innovations, and Baccara and Razin (2009) who argue that innovation bonus to employees could guarantee that innovation takes place.

The second strand of literature focuses on the economic functions of stock options, which are granted to non-executive employees on a large scale basis. A few studies reveal various motives for firms to grant stock options to non-executive employees. For instance, employee stock options can be used by cash-constrained firms as a substitute for cash wages (Core and Guay 2001, Yermack 1995). Employee stock options are tax deductible and hence are able to generate substantial non-debt tax shields (Graham, Lang, and Shackelford 2004, Babenko and Tserlukevich 2009). Firms also use non-executive options to sort and retain certain types of employees. By assuming that employees have heterogeneous beliefs, Oyer and Schaefer (2005)



posit that employee stock options attract optimistic and productive employees who value their firm's stock options more than the market price.

However, the incentive effect of non-executive stock options is still under debate. Oyer (2004) refers to non-executive stock options as “incentives that have no incentive effects”. Because stock options granted to rank-and-file employees reward them for joint performance improvements, free riding stemming from an individual worker's inability to substantially affect option value herself may dominate the positive incentive effect. In contrast, Hochberg and Lindsey (2010) find that the pay-for-performance sensitivity created by employee stock options reinforces the mutual monitoring and cooperation among rank-and-file employees, resulting in better firm operating performance. Our paper adds to this literature by showing that non-executive stock options incentivize rank-and-file employees to be innovative.

Moreover, the convexity of wealth-performance relation, a distinct feature of stock options, promotes risk-taking incentives (Murphy 2003). This feature has received extensive attention in studies on the relation between executive compensation and risk-taking (e.g., Smith and Stulz 1985, Guay 1999, Coles, Daniel, and Naveen 2006, Low 2009). However, few studies examine this feature in the framework of non-executive employee compensation. In a paper contemporaneous to ours, Bova et al. (2012) show that employees who hold stock of their own company have strong incentives to reduce corporate risk because they are risk-averse and have their human capital closely tied to their employer's fortune. Our study, however, shows that when employees hold stock options instead, their risk-taking incentives increase. This feature, together with other features of non-executive stock options, namely failure tolerance, encouraging long-term perspectives, and promoting team-based work, makes non-executive employee stock options an effective stimulator for innovation.

### **III. Data, Variables, and Summary Statistics**

#### *A. Data and Sample*

We obtain data on employee stock options from the Investors Responsibility Research Center (IRRC) Dilution Database, which covers Standard and Poor's (S&P) 1,500 firms between 1997 and 2005. This dataset contains firm-level information on options granted to all employees, including year-end outstanding option grants, the weighted average exercise price and weighted average contractual life of options outstanding, and other characteristics of employee option portfolios. To separate non-executive employee options from executive options, we match the IRRC data with the data from Compustat ExecuComp database. ExecuComp provides information on options outstanding for top executives in a firm. Financial data are from the Compustat Industrial Annual files. Data on stock prices and returns are retrieved from the Center for Research in Security Prices (CRSP) files.

To measure the quantity and quality of innovation output, we use data from the NBER Patent and Citation Database, which provides detailed information on all U.S. patents granted by the U.S. Patent and Trademark Office between 1976 and 2006. There is, on average, a two-year lag between the date when inventors file for patents (the application date) and the date when patents are granted. Since the latest year in the NBER dataset is 2006, patents applied for in 2004 and 2005 may not be completely covered by the database as it only includes patents eventually granted. As suggested by Hall, Jaffe, and Trajtenberg (2001), we end our sample period in 2003 to address this issue.<sup>6</sup>

Following Hirshleifer, Low, and Teoh (2012), we exclude firms in any four-digit SIC industries that have no patents between 1976 and 2006 and firms in financial and utility

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<sup>6</sup> We use the patent application year rather than the grant year to merge the NBER and IRRC databases, since Hall, Jaffe, and Trajtenberg (2001) suggest that the application date, as compared to the grant date, is closer to the actual time of inventions.

industries (SIC code: 6000-6999 and 4900-4999, respectively). Also excluded are firms with missing values for non-executive and executive options and for variables employed in regressions. These restrictions result in a final sample that consists of 1,394 firms (5,640 firm-years) between 1998 and 2003. Our sample starts in 1998 because we use one-year lagged value of non-executive employee stock options when predicting innovation output. Appendix A tabulates the sample construction in greater detail.

### *B. Measuring Innovation Output*

Our first measure of innovation output is the number of patents applied for by a firm in a given year (*Patents*). Patent counts, however, imperfectly capture innovation success because patents vary drastically in their technological and economic significance (Hirshleifer, Low, and Teoh 2012). We therefore follow Hall, Jaffe, and Trajtenberg (2001, 2005) and use forward citations of a patent to measure its quality (importance).<sup>7</sup> The raw citation counts suffer from truncation bias due to the finite length of the sample. As patents receive citations from other patents over a long period of time, patents in the later years of the sample have less time to accumulate citations. We use two methods to deal with this truncation bias. First, we adjust each patent's raw citation counts by multiplying it with the weighting index of Hall, Jaffe, and Trajtenberg (2005) provided in the NBER database. The weighting index is derived from a quasi-structural model, where the shape of the citation-lag distribution is econometrically estimated. *Qcitations* is then the sum of the adjusted citations across all patents applied for during each firm-year. Second, we adjust the raw citation counts using the fixed-effect approach, which involves scaling the raw citation counts by the average citation counts of all patents

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<sup>7</sup> We include self-citations since Hall, Jaffe, and Trajtenberg (2005) find that self-citations are more valuable than external citations. They argue that self-citations, which come from subsequent patents, reflect strong competitive advantages, less need of technology acquisitions, and lower risk of rapid entry.

applied for in the same year and in the same technology class. The fixed-effect approach accounts for the differing propensity of patents in different years and in different technology classes to cite other patents.<sup>8</sup> We use *Tcitations* to denote the sum of the adjusted citations during each firm-year under this alternative adjustment approach.

### *C. Measuring Non-executive Employee Stock Options*

Firms do not explicitly disclose information regarding options granted to non-executive employees. We follow the methodology of Hochberg and Lindsey (2010) when computing the Black-Scholes value of non-executive employee stock options. Specifically, we first use data from the IRRC database to estimate the Black-Scholes value of outstanding options held by all employees.<sup>9</sup> We then estimate the Black-Scholes value of outstanding options held by the top five executives based on the information provided by ExecuComp. Finally, the Black-Scholes value of non-executive employee options is equal to the difference between the value of options for all employees and the value of options for the top five executives. To mitigate heteroscedasticity, we scale the Black-Scholes value of non-executive employee options using the number of non-executive employees. The resulting measure (*EmpOpt*), the per-employee value of non-executive stock options, is the key variable of our interest in the regressions.

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<sup>8</sup> See Atanassov (2012) and Hirshleifer, Low, and Teoh (2012) for detailed discussions on the advantages and disadvantages of this approach.

<sup>9</sup> When calculating the value of non-executive stock options and related incentive measures, we do not use the Black-Scholes inputs in the IRRC database because they are company-supplied inputs and can be biased if firms want to avoid reporting large earnings expenses associated with stock options. Following Hayes, Lemmon, and Qiu (2012), we compute annualized volatility of the past 36 months' monthly stock returns and the dividend yield using the Compustat and CRSP Merged Database. Risk-free rates are retrieved from the Federal Reserve files. All option values are measured at the fiscal year end. Similar to Hochberg and Lindsey (2010), we treat all options as exercisable when calculating their average life to expiration.

#### *D. Control Variables*

To isolate the effect of non-executive employee stock options on innovation output, we control for an array of firm characteristics that have been documented as important determinants of innovation by previous studies. The first control variable is R&D expenses scaled by total assets ( $R\&D/Assets$ ), which serves as an important input to innovation, apart from human capital and the efforts and creativity of managers and employees (Atanassov 2012). Hall and Ziedonis (2001) argue that large firms and capital-intensive firms generate more patents and citations. We thus use the natural log of total assets ( $Ln(Assets)$ ) to control for firm size. Our results are robust to the use of net sales or the number of employees as proxies for firm size. We use the log of the net Property, Plant, and Equipment ( $PPE$ ) scaled by the number of employees ( $Ln(PPE/\#employees)$ ) to account for capital intensity. The log of the net sales scaled by the number of employees ( $Ln(Sales/\#employees)$ ) is included to proxy for labor productivity and quality as higher labor productivity may lead to higher innovation productivity. Return on assets ( $ROA$ ) is included to capture profitability. Also included are *Sales growth* and the market-to-book ratio ( $M/B$ ) as proxies for growth opportunities. The cash-to-assets ratio ( $Cash/Assets$ ) and the leverage ratio ( $Leverage$ ) are added to account for the effects of cash holdings and capital structure on innovation. To control for the effect of a firm's life cycle on its innovation ability, we employ the natural log of firm age,  $Ln(Firm\ age)$ , which is the number of years elapsed since a firm enters the CRSP database.

Additionally, Hirshleifer, Low, and Teoh (2012) find that high innovation productivity is associated with better stock performance. Hence, we include the compounded monthly stock returns over the fiscal year (*Stock return*). Given that Chan, Lakonishok, and Sougiannis (2001) document that R&D investments are positively associated with stock return volatility, we include

the standard deviation of monthly stock returns over the fiscal year (*Stock volatility*) as an additional control. Aghion et al. (2005) document an inverted U-shape relation between product market competition and innovation. Accordingly, similar to Atanassov (2012) and Chemmanur and Tian (2011), we include as control variables the three-digit SIC Herfindahl index and its squared item.

Finally, Francis, Hasan, and Sharma (2011) document that stock options granted to corporate executives have a positive effect on innovation output. Thus, we control for the average value of stock options across the top five executives, *ExeOpt*. All variables are winsorized at the 1% level at both tails of their distributions. Except *Stock return* and *Stock volatility*, which are measured between year  $t-1$  and  $t$ , all control variables are measured at  $t-1$  in the regressions. Dollar values are converted into 2000 constant dollars using the GDP deflator.

### *E. Descriptive Statistics*

Columns (1) to (3) of Table 1 respectively report means, medians, and standard deviations of the variables used for the whole sample. We divide firms into two subsamples according to the median value of options per non-executive employee (*EmpOpt*) each year, and report mean values of the variables in columns (4) and (5) for high and low *EmpOpt* firms separately. We test the mean differences of variables between the two subsamples and report the levels of significance in column (5). Similar inferences are drawn using the *Wilcoxon-Mann-Whitney* test (untabulated) on the differences in median values between the two subsamples.

For our corporate innovation measures, an average firm in our sample applies for roughly 14 patents and receives 46 raw citations for its patents every year. The average citations of patents adjusted based on the weighting scheme of Hall, Jaffe, and Trajtenberg (2001, 2005) (*Qcitations*)

and on the year and technology class fixed effect method ( $T_{citations}$ ) are around 144 and 15, respectively. The distributions of patent and citation counts are highly skewed. Untabulated statistics reveal that approximately 52% (58%) of firms apply for no patents (receive no citations) in a given year, thus the median number of patent (citation) counts is zero.

The distribution of  $EmpOpt$  shows positive skewness as well. On average, each non-executive employee holds about \$50,200 worth of stock options, while the median non-executive employee has roughly \$8,500 worth of stock options. In contrast, options held by an average executive are worth \$7.6 million, 152 times more valuable than those held by an average non-executive employee. However, the total value of options held by all non-executive employees is on average 7.5 times as large as the value of options held by all top five executives, suggesting that more stock options are held by non-executive employees as a whole, rather than by the top five corporate executives.

Firms in the high  $EmpOpt$  subsample, relative to low  $EmpOpt$  firms, are significantly more innovative in terms of the numbers of patents and citations, raw and adjusted. By looking at the mean differences in firm characteristics between the two subsamples, we find that firms with more non-executive employee stock options are younger and have fewer employees, greater growth opportunities, higher capital intensity and labor quality, lower leverage, more cash holdings, and higher but more volatile stock returns. In addition, they make more R&D investments and operate in more competitive industries than their low  $EmpOpt$  counterparts. Although interesting, these unconditional relations require more refined multivariate tests, which we turn to next.

## IV. Main Results

### A. The Baseline Model

We examine the effect of non-executive stock options per employee on a firm's innovation output using the baseline model as follows:

$$\text{Ln}(1+\text{Innovation}_{i,t}) = \alpha + \beta \text{Ln}(1+\text{EmpOpt}_{i,t-1}) + \gamma X_{i,t-1} + \delta \text{Industry} + \theta \text{Year}_t + \varepsilon_{i,t}, \quad (1)$$

where  $\text{Innovation}_{i,t}$  refers to our innovation measures (*Patents*, *Qcitations*, and *Tcitations*) of firm  $i$  in year  $t$ . The key explanatory variable is *EmpOpt*, measured at the end of year  $t-1$ . To reduce skewness of our innovation measures, *EmpOpt*, and *ExeOpt*, we use the log of one plus these variables in the regression analyses.  $X$  represents the set of control variables defined in Section III.D. We also include two-digit SIC industry and year fixed effects in the model.<sup>10</sup> The standard errors of the estimated coefficients allow for clustering of observations by firm but our conclusions are not affected if we allow clustering by both firm and year.

Table 2 reports the results of our baseline regressions in equation (1). We find that *EmpOpt* is positively and significantly associated with all three measures of innovations,  $\text{Ln}(1+\text{Patents})$ ,  $\text{Ln}(1+\text{Qcitations})$ , and  $\text{Ln}(1+\text{Tcitations})$  with  $t$ -statistics of 3.5, 3.5, and 3.7, respectively. Economically, increasing *EmpOpt* from its 25<sup>th</sup> percentile (\$2,722) to the 75<sup>th</sup> percentile (\$33,802) increases the values of *Patents*, *Qcitations*, and *Tcitations* by almost 96%, 141%, and 105% from their respective means.<sup>11</sup> Untabulated statistics show that the mean Variance Inflation Factor (VIF) is below 2, suggesting that multicollinearity is not an issue in our setting.

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<sup>10</sup> Both our innovation measures and *EmpOpt* are highly persistent variables, therefore, we include industry fixed effects rather than firm fixed effects in the regressions. The first order autocorrelations for  $\text{Ln}(1+\text{Patents})$ ,  $\text{Ln}(1+\text{Qcitations})$ ,  $\text{Ln}(1+\text{Tcitations})$ , and  $\text{Ln}(1+\text{EmpOpt})$  are 0.95, 0.89, 0.91, and 0.88, respectively. Zhou (2001) points out that the persistence of key variables can reduce the signal-to-noise ratio and lower the power of panel data estimators.

<sup>11</sup> Because  $d[\text{Ln}(1+y)]/d[\text{Ln}(1+x)] = [(1+x)/(1+y)] dy/dx$ ,  $dy = d[\text{Ln}(1+y)]/d[\text{Ln}(1+x)] \times [(1+y)/(1+x)] dx$ . For example, when quantifying the effect of the change in *EmpOpt* ( $dx$ ) on the change in *Patents* ( $dy$ ), we increase *EmpOpt* from its 25<sup>th</sup> percentile (\$2,722) to the 75<sup>th</sup> percentile (\$33,802), so  $dx = \$31,080$ . The change in *Patents* ( $dy$ ) from its



We find that the value of executive stock options,  $\ln(1+ExeOpt)$ , also has positive effects on innovation, but the coefficients are statistically insignificant ( $t$ -statistics are 0.3, 0.9, and 0.6, respectively, in columns (1)-(3)). In terms of economic significance, increasing  $ExeOpt$  from its 25<sup>th</sup> percentile (\$858,984) to the 75<sup>th</sup> percentile (\$7,623,720) increases the values of  $Patents$ ,  $Qcitations$ , and  $Tcitations$  by 1%, 6%, and 3% from their respective means. Similar results (untabulated) are obtained if we use the value of options held by CEOs, instead of top five executives.<sup>12</sup> Collectively, these results indicate that non-executive employee stock options are more strongly related to innovation than executive options.

The coefficients of other control variables are generally consistent with prior literature. For example, we find that firms with larger R&D expenditures are associated with higher innovation productivity. Larger and older firms have more patents and citations. Firms with lower leverage and firms with higher  $M/B$ , stock return volatility, and stock performance have more innovation outputs.

We perform a number of additional tests to ensure that our main results are robust to alternative model specifications and variable definitions. For the sake of brevity, we only tabulate the coefficients of key variables in Appendix B. In particular, none of the following had a major effect on our results: (a) running negative binomial regressions (instead of OLS

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mean value (13.5) is then equal to  $0.078 \times [(1+13.5)/(1+2,722)] \times 31,080 = 12.9$ , which amounts to 96% of the mean value of  $Patents$ .

<sup>12</sup> More specifically, the coefficients of the value of CEO options are 0.003, 0.008, and 0.003, respectively, in columns (1)-(3). The corresponding  $t$ -statistics are 0.9, 1.6, and 0.9. When investigating the effect of CEO compensation on innovation over the period of 1992-2006, Francis, Hasan, and Sharma (2011) consider the value of CEO's newly granted options and CEO's vested and unvested options. They use the number of patents and the number of citations per patent to measure innovation output. We replicate their results using our sample and their regression models. More importantly, after augmenting their models by including the value of non-executive employee stock options, we find that the coefficients on employee stock options are all significant at the 1% level. These results are available upon request.

regressions) to address the issue that patent and citation counts are non-negative and discrete;<sup>13</sup> (b) defining non-executive employee options using the calibration method of Oyer and Schaefer (2005) to mitigate the concern that our definition of non-executive employees may wrongly include executives other than the top five;<sup>14</sup> (c) scaling total value of non-executive stock options by market capitalization;<sup>15</sup> (d) using the value of newly granted (rather than total) non-executive stock options; (e) replacing  $EmptOpt_{t-1}$  by  $EmptOpt_{t-2}$  in equation (1) to account for the possibility that it may take more than one year for option incentives to take effect; (f) excluding self-citations when defining  $Qcitations$  and  $Tcitations$ ; (g) excluding firm-years with zero patents and citations; (h) using as dependent variable, the average citations per patent (rather than total citations) that measure the average importance of patents; (i) excluding firms engaging in mergers and acquisitions (identified using the SDC M&A database) in the previous two years, to address the concern that firms may acquire patents and citations through takeovers rather than via in-house innovation activities incentivized by stock options.

## B. Endogeneity Issues

Although we document a strongly positive association between non-executive employee stock options and innovation output, the results are potentially subject to two types of endogeneity. The first type is omitted variable bias. While we have controlled for a standard set

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<sup>13</sup> For this test, the dependent variables are the numbers of patents and adjusted citations, rather than their log values. In addition, to control for the time-invariant firm characteristics that can be correlated with innovation output, we use a mean scaling approach (Aghion, Van Reene, and Zingales 2013), which involves including the pre-sample average of patents and citations between 1976 and 1997 in the negative binomial model, and obtain similar results.

<sup>14</sup> Specifically, we assume that the high-level management other than the top five receives an average option grant one-tenth as large as that received by the average executive in the second through fifth compensation rank. But unlike Oyer and Schaefer (2005) who assume that the number of these high-level managers is ten percent of the total number of employees, we follow Kumar, Page, and Spalt (2011) by assuming that the number of high-level managers in a firm can be approximated by the square root of the total number of employees. Kumar, Page, and Spalt (2011) argue that the linear estimation of Oyer and Schaefer (2005) is likely to overstate the number of executives in large firms.

<sup>15</sup> Alternatively, we measure employee incentives using the total number of non-executive stock options scaled by either the number of employees or the number of shares outstanding. Our results remain qualitatively the same.

of variables that have been shown by previous studies to affect innovation, the relation we observe may be spurious if our model omits any variables that affect both corporate innovation and the value of non-executive stock options. The other possible endogeneity issue is reverse causality. For instance, it is possible that innovative firms are more likely to grant stock options to attract or retain talented employees (e.g., Oyer and Schaefer 2005). In both cases, the coefficient estimates from the OLS regressions are biased and inconsistent. To address these endogeneity issues, our first strategy is to explicitly describe issues related to potential omitted variables and reverse causality that we can think of, and design specific tests to address them. We tabulate the results in Table 3. While all control variables in equation (1) are still included in the new tests, we only report the coefficients of  $\text{Ln}(1+\text{EmpOpt})$  and the newly added variables for brevity. In our second strategy, we use the instrumental variables approach to mitigate any remaining endogeneity concerns. The results of the instrumental variables approach are tabulated in Table 4.

### *B.1. Potential Omitted Variables*

The use of stock options for employee compensation can potentially alleviate firms' financial constraints through two channels, i.e., saving cash when options are granted (Core and Guay 2001) and generating substantial cash inflows from the proceeds and associated tax benefits when the options are exercised (Babenko, Lemmon, and Tserlukevich 2011). Thus, to the extent that innovative firms are financially constrained because of pressing investment needs for innovation, they may pay non-executive employees with stock options instead of cash, leading to a positive relation between employee options and innovation output. While we have included cash holdings in equation (1), to further mitigate the concern that financial constraints may drive

our findings, we augment our baseline model by including as additional control variables Hadlock and Pierce's (2010) index of financial constraints, and the proceeds and tax benefits generated by option exercises.<sup>16</sup> The results, reported in Panel A of Table 3, suggest that the effect of financial constraints on innovation is significantly negative, while the impact of option proceeds and tax benefits on innovation is insignificant. More importantly, our main results still hold.

Corporate governance may affect both employee options and corporate innovation. On one hand, entrenched managers may dole out generous stock option packages to employees to buy a quiet life in poorly governed firms (Bertrand and Mullainathan 2003). On the other hand, Chemmanur and Tian (2011) show that firms shielded with a larger number of anti-takeover provisions generate better innovative outcomes because anti-takeover provisions alleviate the short-term pressure on managers from the corporate control market. In addition, while institutional holdings reduce the demand for employee stock options as an incentive scheme (Eisenhardt 1988), Graves (1988) finds that institutional investors negatively affect firm innovation in the computer industry due to their short-termism. To ensure our findings are not driven by corporate governance, we add to equation (1) a set of governance measures, including the governance index (*G-index*) compiled by Gompers, Ishii, and Metrick (2003), board size, and the level of institutional holdings. Panel B of Table 3 reveals that these additional controls do not affect our main results.<sup>17</sup>

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<sup>16</sup> Hadlock and Pierce's (2010) index is defined as  $-0.737 \times \ln(\text{Assets}) + 0.043 \times \ln(\text{Assets})^2 + 0.04 \times \text{Firm age}$ . By construction, higher scores of Hadlock and Pierce's (2010) index indicate that firms are more financially constrained. They show that in various contexts, their index is a more reasonable measure of financial constraints than alternative measures, such as Kaplan and Zingales' (1997) index, Whited and Wu's (2006) constraint index, and the dividend payer indicator. In untabulated results, we also include the three alternative measures and find similar results. Option proceeds and tax benefits are defined according to Babenko, Lemmon, and Tserlukevich (2011) using the IRRC database.

<sup>17</sup> The coefficient of *G-index* is positive but insignificant. This may reflect a mixed effect of *G-index* on innovation productivity since Atanassov (2012) finds that the firms create fewer patents and fewer citations of patents after the

Industry geographic clustering may contribute to the correlation between employee options and innovation. Engelberg, Ozogus, and Wang (2010) show that firms in the same industry cluster exhibit significant correlation in firm fundamentals. Jaffe, Trajtenberg, and Henderson (1993) and Ellison, Glaeser, and Kerr (2010) provide evidence of knowledge spillovers within geographic clusters. Furthermore, Kedia and Rajgopal (2009) show that a firm's option grants to rank-and-file employees are positively affected by the option granting behavior of other firms nearby as firms use stock options to attract and retain employees in tight labor markets. To the extent that the geographic clustering of option programs occur in areas where innovation investments are correlated locally, the relation between employee stock options and innovation may just capture this geographic proximity effect. Although we have controlled for industry fixed effects in the main specification, to further address this concern, we conduct the following tests: (a) removing firms with their headquarters in Silicon Valley where high technology firms have strong propensity to grant stock options to their non-executive employees and excluding all firms located in industry clusters defined by Kedia and Rajgopal (2009);<sup>18</sup> (b) directly controlling for geographic fixed effects using two digit ZIP codes. The results tabulated in Panels C and D, respectively, confirm that our main results are unaffected.

Finally in untabulated tests, we also control for a few variables that may affect non-executive employee options and firm innovation. They are the top five executives' stock ownership (Cai et al. 2010), CEO tenure, abnormal stock returns (CAPM adjusted) accumulated over the period [ $t-3, t-1$ ] as a proxy for management quality (Milbourn 2003) or employee sentiment (Bergman and

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enactment of anti-takeover laws in certain states, highlighting the agency issue in the corporate innovative activities. Consistent with Atanassov (2012), the board size has a negative and significant coefficient. However, the coefficient of institutional ownership is negative and insignificant in most regressions. This may be due to the mixed effect of institutional ownership on innovative outcomes since in addition to the negative effect of institutional investors' short-termism on innovations, Aghion, Van Reenen, and Zingales (2013) find that institutional owners can encourage innovation efficiency by reducing managers' career concern on risky projects.

<sup>18</sup> Following Gompers, Lerner, and Scharfstein (2005), we define Silicon Valley as the Alameda, San Mateo, and Santa Clara counties in California.

Jenter 2007), labor expenses per employee measured at the three-digit SIC industry level, and the level of employee stock ownership in defined contribution pension plans, as obtained from the IRS (Internal Revenue Service) Form 5500 database. While the inclusion of these variables significantly reduces the number of observations owing to data availability, it does not affect our main findings.

### *B.2. Tests for Reverse Causality – Stock Options Used for Attracting Innovative Employees*

The causal relation between non-executive employee options and innovation can be bidirectional. While our results suggest that employee stock options enhance firm innovation, innovative firms may grant stock options to employees for purposes that are not directly related to innovation enhancement. Core and Guay (2001) show that employee stock options can be used to attract and retain certain types of employees. For example, innovative firms may grant options to more educated employees who may understand options better and be more willing to accept options as a form of compensation, to less risk-averse employees, or to employees with strong gambling preference because these employees may find options more in line with their risk attitude (Kumar, Page, and Spalt 2011), or to employees who are more optimistic about their employers' prospects.

In addition, Oyer (2004) and Oyer and Schaefer (2005) point out that firms use stock options to retain employees by indexing their compensation to outside opportunities, which are positively correlated with their employer's stock price. Because US labor markets are geographically segmented, rank-and file employees' outside opportunities mainly come from other firms located in the same geographical area. Thus, Kedia and Rajgopal (2009) find that the

retention role of employee options is more effective when a firm's stock price co-moves more with stock prices of other firms in the same region.

The two directions of causality are not necessarily mutually exclusive. To substantiate forward causality (employee options enhancing innovation) while accounting for reverse causality (innovative firms paying employee more options), we incorporate into equation (1) several additional variables that capture firms' sorting and retention motives behind the use of employee stock options. Specifically, we include the percentage of the population in the local county with college education as a proxy for rank-and-file employees' average education level. We control for the local religiosity, a proxy for employee risk aversion (Hilary and Hui 2009) and the Catholic-Protestant ratio, a proxy for employee gambling propensity (Kumar, Page, and Spalt 2011).<sup>19</sup> We add the median abnormal (CAPM adjusted) stock return across all firms sharing the same two-digit zip code, as a proxy for regional employee sentiment (Kedia and Rajgopal 2009). Also included is Kedia and Rajgopal's (2009) local beta, which measures the extent of co-movement between a firm's stock price and stock prices of other firms in the same region.<sup>20</sup> The results, reported in Panel E of Table 3, reveal that  $\text{Ln}(1+\text{EmpOpt})$  remains positive and significant, indicating that forward causality is robust after we explicitly account for reverse causality.

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<sup>19</sup> The county-level religion data is collected from the American Religion Data Archive (ARDA). Since the county level religion data is available only for years 1990 and 2000, following Hilary and Hui (2009), we linearly interpolate the religion data to obtain the values in the intermediate years. Religiosity is defined as the proportion of religious adherents in a county. Following the classification provided by ARDA, we categorize the churches into four main groups, including Catholics, Protestants, Orthodox, and others. We define the Catholic-Protestant ratio as the ratio of the number of Catholic adherents in the county to the number of Protestant adherents in the county.

<sup>20</sup> Local beta,  $\beta^{LOC}$ , is estimated using the equation,  $R_t^i = \alpha_i + \beta^{LOC} R_t^{LOC} + \beta^{MKT} R_t^{MKT} + \beta^{IND} R_t^{IND}$ , where  $R^i$  is a firm's monthly stock return,  $R^{LOC}$  is the monthly return of an equally weighted index in the stock's corresponding MSA (Metropolitan Statistical Area). To alleviate the concern of spurious correlations, we exclude the return of the corresponding stock when calculating  $R^{LOC}$ .  $R^{MKT}$  is the monthly return of the equally weighted CRSP market portfolio.  $R^{IND}$  is the monthly return of an equally weighted index of the stock's corresponding 49 Fama-French industries. We estimate the above equation using time-series regressions over three different periods, 1993-1997, 1998-2002 and 2003-2007 and using firms with at least 24 non-missing monthly return observations. Our results are robust to using two-digit SIC codes as industry classifications.

### B.3. The Instrumental Variables Approach

To further address endogeneity concerns, especially those not specifically identified previously, we employ an instrumental variables approach similar to that of Hochberg and Lindsey (2010). In particular, we use two instrumental variables that are correlated with option grants to non-executive employees but unrelated to innovation output. The first instrument is the average per-employee value of annual option grants to non-executive employees across all zero-citation firms that share the same two-digit ZIP code with the firm but do not belong to the firm's two-digit SIC industry, *EmpOpt\_Other*. When constructing this instrument, we use firms in geographical proximity because Kedia and Rajgopal (2009) document a local similarity in the employee option grant policy. Therefore, our instrument satisfies the relevance criteria. Furthermore, we only include non-innovative (zero-citation) firms in other industries to avoid local knowledge spillovers among firms within the same industry geographic cluster (e.g., Jaffe, Trajtenberg, and Henderson 1993) and among innovative firms across industries. Thus our instrument should satisfy the exclusion criteria as well.<sup>21</sup> Taken together, we expect *EmpOpt\_Other* to affect a firm's innovation outcomes only through the resemblance of employee compensation policy in the neighborhood, rather than through knowledge spillovers within and across industries.

The second instrument is the log of the number of shares outstanding for the firm,  $\ln(\text{Number of shares})$ . Firms with large option programs may have a large number of shares outstanding due to option exercises, while the number of shares outstanding should have no

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<sup>21</sup> The results are qualitatively the same if we define *EmpOpt\_Other* using zero-R&D firms, firms in non-high-tech industries (Loughran and Ritter 2004), or firms in non-new-economy industries (Murphy 2003).



effects on firm innovation other than its indirect effect through employee stock option values (Hochberg and Lindsey 2010).<sup>22</sup>

Results obtained using the instrumental variables approach in the framework of a two-stage least squares (2SLS) regression are reported in Table 4. The first stage regression is presented in column (1).  $\ln(1+EmpOpt\_Other)$  is significantly and positively related to  $\ln(1+EmpOpt)$  ( $t$ -statistic = 4.7). The number of shares outstanding significantly and positively predicts  $\ln(1+EmpOpt)$  with a  $t$ -statistic of 6.5. The instruments also pass the relevance test as the  $F$ -statistic from the joint test of excluded instruments is 36 and significant at the 1% level. The over-identification tests also support the validity of these instrumental variables as  $p$ -values for the  $J$ -statistics are all larger than 0.1.

Columns (2) to (4) show the second stage of the 2SLS regressions for each of the three dependent variables. Similar to the OLS regressions, we find that employee stock options significantly and positively predict patent counts and adjusted citation counts. In untabulated tests, we alternatively include only one of the two instruments in the 2SLS regressions and find that the results remain qualitatively the same.<sup>23</sup> We also estimate the 2SLS model using the methods of limited information maximum likelihood (LIML) and generalized method of moments (GMM), and find that our results are unaffected by these alternative methods.

Taken together, our results in Section IV suggest that non-executive employee stock options form an effective group incentive that induces employees to be innovative and enhances the innovation productivity in a firm.

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<sup>22</sup> Hochberg and Lindsey (2010) use the number of employees as an additional instrument. We cannot do the same as we have used the variable to scale the value of employee options.

<sup>23</sup> Each instrument individually passes the relevance test. The  $F$ -statistics from the joint tests of excluded instruments are 24 and 45 for  $\ln(1+EmpOpt\_Other)$  and the number of shares outstanding, respectively. The corresponding  $p$ -values are both less than 0.01.

## V. Further Analysis

### A. Cross-sectional Heterogeneity in Results

To further understand the channels through which non-executive employee stock options affect corporate innovation, we partition our sample in several ways to examine whether our results vary across firms. We report the results in Table 5 where the regressions include all the control variables in Table 2. Again, to save space, we only tabulate the coefficients of  $\ln(1+EmpOpt)$  for different subsamples.

#### A.1. Importance of Employee's Input to Innovation

Given that skills and efforts of employees are fundamental inputs to the innovation process, we expect that employee incentives provided by stock options have a stronger impact on the innovation productivity in firms where the input of rank-and-file employees are relatively more important. We use the employee treatment index in the KLD Database and per-employee R&D expenses to measure the importance of employees for innovation. Bae, Kang, and Wang (2011) argue that firms are more likely to adopt employee friendly policy if they value employees' firm-specific human capital. Ouimet and Zarutskie (2011) point out that labor and human capital play increasingly important roles in production, especially in the R&D intensive industries. Thus, employee treatment and per-employee R&D expenses should be positively related to employee importance in innovation.

In Panel A of Table 5, we partition the firms into two groups using the employee treatment index and per-employee R&D expenses.<sup>24</sup> We classify firms with employee treatment index

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<sup>24</sup> We follow Bae, Kang, and Wang (2011) and construct the employee treatment index ranging from zero to five. The employee treatment index covers the strength in five categories of employee relations, namely, union relations, cash profit-sharing, employee involvement, retirement benefits strength, and health and safety. A higher value of employee treatment index indicates better employee treatment. The median value of the index is zero.

equal to (greater than) zero or with R&D per-employee below (above) the sample median as having low (high) employee importance. We then re-estimate equation (1) for the two groups separately. The results show that the positive relation between employee options and innovation is more pronounced in firms with higher employee treatment index or higher R&D per employee, confirming our conjecture that the positive effect of employee stock options on innovation productivity is stronger if employee inputs are more important and valued. Among firms with low employee importance, the coefficients on employee options are not significantly different from zero and are much smaller in magnitude.

#### *A.2. Free-riding among Employees*

Innovation projects involve various types of tasks and processes, and thus are rarely the task of one individual or a single department. Instead, the use of team-based work is a popular mechanism for enhancing innovation. While we have shown that employee stock options form a strong group-based incentive device to foster innovation, the power of this group incentive can be diluted if free-riding problems are severe among non-executive employees (Hochberg and Lindsey 2010). Therefore, we expect that the positive impact of non-executive stock options on innovation is more pronounced for firms with a less severe free-riding problem. Hochberg and Lindsey (2010) argue that the extent of free-riding is smaller in firms with fewer employees since the overall firm success is more sensitive to the actions of individual workers, and in firms with higher per-employee growth opportunities where the ability of individual employees to influence the firm value is higher (Core and Guay 2001). We thus partition firms into subsamples using the number of employees and per-employee growth opportunities as proxies

for the extent of free riding among employees.<sup>25</sup> Firms with above (below) median number of employees or below (above) median per-employee growth opportunities are defined as having high (low) risk of free-riding. The results, reported in Panel B of Table 5, indicate that the effect of employee options on innovation is indeed stronger among firms with low risk of free-riding problems. More importantly, the finding that our main results are contingent on the extent of free-riding suggests that employee stock options affect corporate innovation at least partially through a group effort channel.

### *A.3. Broad-based vs. Targeted Non-executive Stock Option Plan*

To foster innovation, stock options can be broadly granted to most if not all employees (typically more than 50% of all employees), or selectively targeted towards specific R&D workers or groups. Hochberg and Lindsey (2010) point out that broad-based non-executive option plans, as a group incentive that rewards joint success, may enhance cooperation and mutual monitoring among employees in firms for which knowledge sharing is important. Given the importance of cooperation and mutual monitoring in fostering innovation, we expect the effect of employee stock options on innovation to be stronger in firms that grant options broadly.

We follow Oyer and Schaefer (2005) and Hochberg and Lindsey (2010) when identifying broad-based stock option plans. Specifically, we exclude option grants to high-level management (including the top five executives) from the total grants to all employees using the calibration method described in Section IV.A, and obtain the residual grants to non-executive employees. We then classify option programs as broad-based (targeted) if the residual grants to non-executive employees is greater (less) than 0.5% of the number of shares outstanding.

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<sup>25</sup> We follow Core and Guay (2001) and define per-employee growth opportunities as (market value of equity - book value of equity)/the number of employees.

We separately estimate equation (1) for firms with targeted and broad-based option plans and report the results in Panel C of Table 5. The coefficients of  $\ln(1+EmpOpt)$  are highly positive and significant for firms with broad-based option plans, but are much smaller and statistically insignificant for firms with targeted option plans. This finding is consistent with the notion that broad-based option plans promote joint success, encourage cooperation and mutual monitoring among rank-and-file employees, and alleviate free-riding incentives, leading to greater innovation productivity.

#### *A.4. Average Stock Option Expiration Period*

Due to the delayed feedback nature of innovation activities, Manso (2011) argues that the optimal incentive contract for innovations must provide the agent with long-term incentives. Therefore, we expect the positive effect of employee stock options on innovative outcomes to be stronger if non-executive employee options have a longer average expiration period.

To explore this possibility, we split our sample into two groups based on the median length of the Black-Scholes-value-weighted average expiration period across all stock options in a firm.<sup>26</sup> The regression results for the two subsamples, tabulated in Panel D of Table 5, are consistent with our expectation. The effect of  $\ln(1+EmpOpt)$  on innovation output is more evident in firms of which stock options have a longer expiration period, indicating that long expiration periods of employee stock options induce long-term commitment by employees, prevent employees' myopic behaviors, and thus enhance innovation efficiency.

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<sup>26</sup> The median and mean values of average expiration periods for our sample are 6.9 and 6.7 years, respectively.

#### *A.5. Employee Stock Ownership*

Employees bear substantial amounts of undiversified risk by holding employer stocks especially when they already invest large amounts of human-capital into the firm (Poterba 2003; Berk, Stanton, and Zechner 2008). Consistent with this view, Faleye, Mehrotra, and Morck (2006) and Bova et al. (2012) find that firms with large employee ownership have strong incentives to reduce firm risk. Given the importance of risk-taking incentives in corporate innovative activities, we expect the incentive effect of employee stock option on innovation to be stronger in firms with lower employee ownership where employees' risk aversion is lower.

We hence divide our sample based on whether firms have investments in their own stocks for their employees in the defined contribution pension plans reported in the IRS Form 5500 and estimate equation (1) for both subsamples. The results are reported in Panel E of Table 5. Consistent with our expectation, the positive effect of employee options on innovation is more evident in firms that have no investments in their own stocks for their employees, suggesting that employee stock options are more effective in promoting risk-taking when employees are less risk-averse.

#### *B. The Impact of Non-executive Employee Options on R&D Activities*

So far, we have examined the effects of non-executive stock options on innovation outputs as measured by patents and citations of patents. In this section, we examine how non-executive employee stock options affect R&D activities, which are key inputs to the innovation process. To this end, we regress two measures of R&D activities namely, R&D intensity, measured as the natural log of one plus R&D expenses per employee ( $\ln(1+R\&D/\#employees)$ ) and  $R\&D/Assets$ , on  $\ln(1+EmpOpt)$  and the same set of control variables used in Table 2. We set R&D measures

equal to zero if R&D expenses are missing in Compustat. To account for the differences between firms who report R&D and those who do not, we include in the regressions an indicator (*RNDD*) which equals one if R&D expenses are missing, and zero otherwise. In untabulated tests, we obtain similar results if we exclude firms with missing R&D from our analysis.

The results in Table 6 show a significantly positive effect of non-executive stock options on both R&D measures, suggesting that employee stock options are associated with increased investments in innovation. The effect is also economically significant: increasing *EmpOpt* from its 25<sup>th</sup> percentile to the 75<sup>th</sup> percentile increases *R&D/Assets* and  $\ln(1+R\&D/\#employees)$  by approximately 222% and 219%, from their respective means.

### *C. Employee Option Delta and Vega*

Last but not least, we examine whether non-executive employee stock options affect innovation through option delta or vega. Employee stock options increase not only the sensitivity (delta) of employees' wealth to stock prices, but also the sensitivity (vega) of employees' wealth to stock volatility. Although a high delta can encourage employees to work hard, it can also affect employees' attitude toward risk and lead to too little risk-taking (Hirshleifer and Suh 1992). Guay (1999) highlights the need to differentiate between the incentive effects of option delta and vega. He points out that increased delta exposes employees to more risk, while increased vega helps offset the aversion to risky projects that arises due to the increased delta.

To break down the incentive effects of employee stock options, we compute employee stock options' delta and vega, i.e., the slope and convexity, respectively, of the relation between the value of employee options and stock price. Specifically, using the IRRC database, we define

non-executive employee option delta (*EmpDelta*) as the dollar change in non-executive option values for a 1% change in stock price, deflated by the number of non-executive employees. Non-executive employee option vega (*EmpVega*) is the dollar change in non-executive option value for a 1% change in stock return volatility, deflated by the number of non-executive employees.<sup>27</sup> We then use  $\ln(1+EmpDelta)$  and  $\ln(1+EmpVega)$  to replace  $\ln(1+EmpOpt)$  in equation (1) and perform the regression analysis. In the meantime, we also replace  $\ln(1+ExeOpt)$  with the average delta and vega of the top five executives' stock-based compensation, which are denoted as  $\ln(1+ExeDelta)$  and  $\ln(1+ExeVega)$ , respectively. Other control variables are the same as those reported in Table 2.

Table 7 presents the regression results. Non-executive employee delta,  $\ln(1+EmpDelta)$ , has a positive but statistically insignificant effect on patents and citations. In contrast, the effect of employee vega is positive and statistically significant with *t*-statistics of 4.4, 4.2, and 3.9, respectively. Turning to economic significance, increasing *EmpVega* from its 25<sup>th</sup> percentile (\$31.0) to the 75<sup>th</sup> percentile (\$242.3) increases the values of *Patents*, *Qcitations*, and *Tcitations* by almost 68%, 102%, and 64% from their respective means. Taken together, the horse race between employee delta and vega reveals that it is the convexity, rather than the slope, of the relation between employee options and stock prices that drives the effect of employee options on corporate innovation.

Furthermore, consistent with Francis, Hasan, and Sharma (2011), we find that executive delta has no significant effect on innovation output. While coefficients of executive vega are all positive in our regressions, they are statistically insignificant (*t*-statistics are 0.9, 1.5, and 1.1,

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<sup>27</sup> Similar results are obtained if we compute employee delta using all forms of employee stock-based compensation, including stock options and stock holdings in the defined contribution pension plans.



respectively).<sup>28</sup> In terms of economic significance, increasing *ExeVega* from its 25<sup>th</sup> percentile (\$7,797) to the 75<sup>th</sup> percentile (\$56,999) increases the values of *Patents*, *Qcitations*, and *Tcitations* by roughly 5%, 11%, and 5% from their respective means. Consistent with our findings in Table 2 where we use both non-executive and executive stock option in regressions, these results appear to suggest that more stock options should be granted to non-executive employees, rather than to executives, in order to fuel corporate innovation.

## **VI. Summary and Conclusion**

Innovation has become a core strategy to enhance a firm's competitiveness in the new millennium. As such, how to design an appropriate incentive mechanism to foster innovation productivity constitutes a challenge to firms' innovation practice. Despite abundant literature on various factors that spur or impede innovations, few studies examine the role of employees and employees' incentive scheme in the innovation process. Our paper fills this gap.

Using a large sample of firms covered by the IRRC Dilution Database, the ExecuComp, and the NBER Patent and Citation Database between 1993 and 2003, we document a positive effect of non-executive employee stock options on innovation output, which is measured using the numbers of patents and patent citations, after we control for the R&D expenditure in the regressions. These results are robust to a variety of tests on model specifications, variable definitions, and endogeneity issues. Moreover, we find that the positive effect of non-executive options on innovation is more pronounced in firms where employees' input to innovation is more important, in firms where free-riding among employees is weaker, in firms with broad-based option plans, in firms where options have a longer average expiration period and in firms with

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<sup>28</sup> Similar results (untabulated) are obtained if we use delta and vega of CEO, rather than those of all top five executives.

lower employee stock ownership. Additional analysis reveals that non-executive employee stock options foster innovation through enhancing employees' risk-taking incentives (vega).

Collectively, our findings highlight the role of rank-and-file employees as important innovators, and thus enrich the stakeholder theory of corporate finance. Furthermore, our findings complement Hochberg and Lindsey (2010) by identifying a new channel through which non-executive employee stock options exert a beneficial influence on firm success.

## Appendix A: Sample construction

This table contains the observation counts for the sample at different stages of construction. We start from all firms reported in the IRRC Dilution Database during 1997 to 2005 and merge it with Compustat, CRSP, and ExecuComp. The combined dataset is then merged with the NBER Patent and Citation Database. For the ExecuComp data, we remove firms with unidentified CEOs, negative CEO tenure, missing total compensation (ExecuComp data item *tdc1*), or zero total compensation. Also excluded are firms with less than two top executives in a given year (Spalt 2012). For the NBER Patent and Citation data, we exclude firms in industries that have no patent in any year in the entire database.

Order	Selection criteria	Data source	Period	Number of observations
(1)	Remove observations with missing values on employee stock option variables.	IRRC Dilution Database	1997 - 2005	12,674
(2)	Remove firms without stock prices at year end from Compustat, 36 months of stock return data from CRSP to calculate stock return volatility, or other Black-Scholes (BS) formula inputs	IRRC Dilution Database, Compustat, and CRSP	1997 - 2005	12,384
(3)	Merge with ExecuComp and remove observations of error and firms with less than two top executives in a given year	IRRC Dilution Database, Compustat, CRSP, and ExecuComp	1997 - 2005	12,260
(4)	Merge with NBER Patent and Citation Database and remove firms with missing values for the lagged non-executive options	IRRC Dilution Database, Compustat, CRSP, ExecuComp, and NBER Patent and Citation Database	1998 - 2003	7,386
(5)	Drop financial and utilities and firm-years with missing values for dependent variables	IRRC Dilution Database, Compustat, CRSP, ExecuComp, and NBER Patent and Citation Database	1998 - 2003	5,781
(6)	Remove firms with missing value for control variables used in regressions	IRRC Dilution Database, Compustat, CRSP, ExecuComp, and NBER Patent and Citation Database	1998 - 2003	5,640

## Appendix B: Robustness checks on alternative model specifications and variable definitions

All regressions include the same control variables as those used in Table 2, but the coefficients on these variables are not tabulated. Detailed variable definitions are in the legend of Table 2. The  $t$ - or  $z$ -statistics in parentheses are calculated from the Huber/White/Sandwich heteroskedastic consistent errors, which are also corrected for correlation across observations for a given firm. The symbols \*\*\*, \*\*, and \* denote significance at the 1%, 5%, and 10% levels, respectively.

(a): Negative binomial regressions without log-transforming dependent variables (N = 5,640)			
	<i>Patents</i>	<i>Qcitations</i>	<i>Tcitations</i>
$Ln(1+EmpOpt)$	0.077** (2.1)	0.095** (2.0)	0.082* (1.7)
(b): Using Oyer and Schaefer's (2005) calibrated value of non-executive stock options per employee, <i>EmpOpt_OS</i> (N = 5,640)			
	$Ln(1+Patents)$	$Ln(1+Qcitations)$	$Ln(1+Tcitations)$
$Ln(1+EmpOpt_OS)$	0.024*** (2.9)	0.036*** (2.8)	0.027*** (3.2)
(c): Scaling total value of non-executive stock options by market capitalization, <i>EmpOpt_MC</i> (N = 5,640)			
	$Ln(1+Patents)$	$Ln(1+Qcitations)$	$Ln(1+Tcitations)$
$Ln(1+EmpOpt_MC)$	0.065** (2.4)	0.101** (2.3)	0.067** (2.3)
(d): Using the value of newly granted non-executive stock options, <i>EmpOpt_New</i> (N = 4,437)			
	$Ln(1+Patents)$	$Ln(1+Qcitations)$	$Ln(1+Tcitations)$
$Ln(1+EmpOpt_New)$	0.077*** (2.7)	0.115*** (2.6)	0.089*** (3.0)
(e) Replacing $EmpOpt_{t-1}$ by $EmpOpt_{t-2}$ (N = 4,245)			
	$Ln(1+Patents)$	$Ln(1+Qcitations)$	$Ln(1+Tcitations)$
$Ln(1+EmpOpt_{t-2})$	0.056** (2.2)	0.087** (2.3)	0.062** (2.4)
(f) Excluding self-citations when defining <i>Qcitations</i> and <i>Tcitations</i> (N = 5,640)			
		$Ln(1+Qcitations)$	$Ln(1+Tcitations)$
$Ln(1+EmpOpt)$		0.085*** (2.6)	0.063*** (2.9)
(g) Excluding firm-years with zero patents and citations ( $N_{Patent} = 2,732$ ; $N_{Citation} = 2,342$ )			
	$Ln(1+Patents)$	$Ln(1+Qcitations)$	$Ln(1+Tcitations)$
$Ln(1+EmpOpt)$	0.086*** (3.3)	0.147*** (4.1)	0.121*** (3.9)
(h) Using average citations per patent as dependent variables (N = 5,640)			
		$Ln(1+Qcitations)$	$Ln(1+Tcitations)$
$Ln(1+EmpOpt)$		0.031** (2.0)	0.012** (2.0)
(i) Excluding firms engaging in mergers and acquisitions in the previous two years (N = 1,793)			
	$Ln(1+Patents)$	$Ln(1+Qcitations)$	$Ln(1+Tcitations)$
$Ln(1+EmpOpt)$	0.087*** (3.1)	0.114** (2.5)	0.085*** (2.8)

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**Table 1: Summary statistics**

The sample consists of firms jointly covered in the IRRIC Dilution Database, the ExecuComp, and the NBER Patent and Citation Database between 1998 and 2003. The high (low) *EmpOpt* subsample contains firms with above (below)-median values of *EmpOpt* in each year. *EmpOpt* is value of non-executive stock options per employee. *ExeOpt* is average value of stock options across the top five executives. *Qcitations* and *Tcitations* are patent citations adjusted using the weighting index of Hall, Jaffe, and Trajtenberg (2001) and the method of time-technology class fixed effect, respectively. *Assets* is book value of total assets. *PPE/#employees* is net Property, Plant, and Equipment (*PPE*) scaled by the number of employees. *Sales/#employees* is net sales scaled by the number of employees. *ROA* is EBITDA/*Assets*. *Sales growth* is change in net sales scaled by lagged net sales. Market-to-book ratio (*M/B*) is (*Assets* + Market value of equity - Book value of equity)/*Assets*. *Cash/Assets* is cash-to-assets ratio. *Leverage* is (Short-term debt + Long-term debt)/*Assets*. *Firm Age* is the number of years elapsed since a firm enters the CRSP database. *R&D/Assets* is R&D expenses scaled by book value of total assets. *Stock return* is compounded monthly stock returns over the fiscal year. *Stock volatility* is standard deviation of monthly stock returns over the fiscal year. *Herfindahl* index is computed based on the three-digit SIC code. All variables are winsorized at the 1% level at both tails of the distribution. Dollar values are converted into 2000 constant dollars using the GDP deflator. *T*-tests are conducted to test for differences in means values between the high and low *EmpOpt* subsamples. The symbols \*\*\*, \*\*, and \* indicate that subsample means are significantly different from each other at the 1%, 5%, and 10% levels, respectively.

	Whole sample			High	Low
	<i>N</i> = 5,640			<i>EmpOpt</i> <i>N</i> = 2,819	<i>EmpOpt</i> <i>N</i> = 2,821
	Mean	Median	SD	Mean	Mean
	(1)	(2)	(3)	(4)	(5)
Number of patents (raw)	13.5	0	28.2	16.7	10.3***
Number of citations (raw)	45.7	0	135.0	62.3	29.0***
<i>Qcitations</i>	143.5	0	346.8	189.9	97.3***
<i>Tcitations</i>	14.9	0	32.4	18.9	10.9***
Options per employee ( <i>EmpOpt</i> ) in \$1,000	50.2	8.5	119.0	97.1	3.3***
Options per executive ( <i>ExeOpt</i> ) in \$1,000	7,639	2,716	13,092	11,348	3,933***
Total employee options in \$millions	287.5	55.5	956.1	502.6	72.6***
Total executive options in \$millions	38.2	13.6	65.5	56.7	19.7***
<i>Assets</i> (\$millions)	4,910	1,277	10,006	4,937	4,884
Number of Employees (in 1,000)	17.9	6.1	27.5	11.5	24.3***
<i>Firm age</i> (years)	23.4	17.0	17.9	18.4	28.3***
<i>R&amp;D/Assets</i>	0.04	0.01	0.06	0.06	0.01***
<i>PPE/#employees</i> (in \$1,000)	149.7	46.9	412.9	215.7	83.7***
<i>Sales/#employees</i> (in \$1,000)	322.6	224.0	354.7	414.9	230.4***
<i>ROA</i>	0.10	0.10	0.11	0.10	0.10
<i>M/B</i>	2.30	1.66	1.97	3.06	1.54***
<i>Sales growth</i>	0.13	0.07	0.36	0.19	0.07***
<i>Leverage</i>	0.22	0.23	0.17	0.18	0.27***
<i>Cash/Assets</i>	0.14	0.05	0.18	0.21	0.06***
<i>Stock volatility</i>	0.03	0.03	0.01	0.04	0.03***
<i>Stock return</i>	0.13	0.05	0.58	0.15	0.11**
<i>Herfindahl</i> index	0.18	0.12	0.16	0.14	0.21***



**Table 2: Effects of non-executive stock options per employee on innovation output**

The sample consists of firms jointly covered in the IRRIC Dilution Database, the ExecuComp, and the NBER Patent and Citation Database between 1998 and 2003. *EmpOpt* is value of non-executive stock options per employee. *ExeOpt* is average value of stock options across the top five executives. *Patents* is the number of patents applied for. *Qcitations* and *Tcitations* are patent citations adjusted using the weighting index of Hall, Jaffe, and Trajtenberg (2001) and the method of time-technology class fixed effect, respectively. *Assets* is book value of total assets. *PPE/#employees* is net Property, Plant, and Equipment (*PPE*) scaled by the number of employees. *Sales/#employees* is net sales scaled by the number of employees. *ROA* is EBITDA/*Assets*. *Sales growth* is change in net sales scaled by lagged net sales. *M/B* is (*Assets* + Market value of equity - Book value of equity)/*Assets*. *Cash/Assets* is cash-to-assets ratio. *Leverage* is (Short-term debt + Long-term debt)/*Assets*. *Firm Age* is the number of years elapsed since a firm enters the CRSP database. *R&D/Assets* is R&D expenses scaled by book value of total assets. *Stock return* is compounded monthly stock returns over the fiscal year. *Stock volatility* is standard deviation of monthly stock returns over the fiscal year. *Herfindahl* index is computed based on the three-digit SIC code. Constant terms are included but not reported. The symbols \*\*\*, \*\*, and \* denote significance at the 1%, 5%, and 10% levels, respectively. The *t*-statistics in parentheses are calculated from the Huber/White/Sandwich heteroskedastic consistent errors, which are also corrected for correlation across observations for a given firm. The symbols \*\*\*, \*\*, and \* denote significance at the 1%, 5%, and 10% levels, respectively.

	<i>Ln(1+Patents)</i>	<i>Ln(1+Qcitations)</i>	<i>Ln(1+Tcitations)</i>
	OLS (1)	OLS (2)	OLS (3)
<i>Ln(1+ EmpOpt)</i>	0.078*** (3.5)	0.123*** (3.5)	0.086*** (3.7)
<i>Ln(1+ ExeOpt)</i>	0.001 (0.3)	0.007 (0.9)	0.003 (0.6)
<i>R&amp;D/Assets</i>	6.184*** (8.6)	9.976*** (8.3)	6.079*** (8.0)
<i>Ln(Assets)</i>	0.537*** (19.0)	0.775*** (17.7)	0.547*** (18.4)
<i>Ln(Firm age)</i>	0.121*** (2.7)	0.164** (2.4)	0.111** (2.4)
<i>Ln(PPE/#employees)</i>	-0.029 (-0.7)	-0.033 (-0.5)	-0.028 (-0.6)
<i>Ln(Sales/#employees)</i>	-0.074 (-1.5)	-0.104 (-1.3)	-0.084 (-1.6)
<i>ROA</i>	1.127*** (4.3)	1.821*** (4.1)	1.089*** (3.8)
<i>M/B</i>	0.037*** (2.6)	0.073*** (2.9)	0.047*** (2.9)
<i>Sales growth</i>	-0.216*** (-4.5)	-0.318*** (-3.9)	-0.220*** (-4.5)
<i>Leverage</i>	-0.488** (-2.5)	-0.773** (-2.5)	-0.515** (-2.5)
<i>Cash/Assets</i>	0.126 (0.6)	0.054 (0.2)	-0.005 (-0.0)
<i>Stock volatility</i>	4.257** (2.2)	8.390*** (2.6)	5.562*** (2.6)
<i>Stock return</i>	0.099*** (3.8)	0.201*** (4.1)	0.122*** (4.1)
<i>Herfindahl</i>	0.219 (0.4)	0.505 (0.6)	0.124 (0.2)
<i>Herfindahl</i> <sup>2</sup>	-0.027 (-0.1)	-0.022 (-0.0)	0.140 (0.2)
Industry and year fixed effects	Y	Y	Y
N/R-squared	5,640/0.53	5,640/0.50	5,640/0.49

**Table 3: Tests for omitted variables and reverse causality**

All regressions include the same control variables as those used in Table 2, but their coefficients are not tabulated. Hadlock and Pierce's (2010) index is  $-0.737 \times \text{Ln}(\text{Assets}) + 0.043 \times \text{Ln}(\text{Assets})^2 + 0.04 \times \text{Firm age}$ . Option proceeds and tax benefits are defined using the IRRC Dilution database. An industry cluster is defined as one if 10% of the industry's market value is located in the Metropolitan Statistical Area (MSA) and 10% of the market value of that MSA is accounted for by that industry. Geographic fixed effects are defined using two-digit ZIP codes. Catholic-Protestant ratio is the number of catholic adherents in a county divided by the number of Protestant adherents in that county. Religiosity is defined as the proportion of religious adherents in a county. Median abnormal stock returns are computed across all firms sharing the same two-digit zip code. Local beta is defined according to Kedia and Rajgopal's (2009). Other variable definitions are in the legend of Table 2. The *t*- or *z*-statistics in parentheses are calculated from the Huber/White/Sandwich heteroskedastic consistent errors, which are also corrected for correlation across observations for a given firm. The symbols \*\*\*, \*\*, and \* denote significance at the 1%, 5%, and 10% levels, respectively.

	<i>Ln(1+Patents)</i>	<i>Ln(1+Qcitations)</i>	<i>Ln(1+Tcitations)</i>
	(1)	(2)	(3)
<i>Panel A: Controlling for financial constraints (N = 5,106)</i>			
<i>Ln(1+ EmpOpt)</i>	0.076*** (3.1)	0.117*** (3.0)	0.082*** (3.1)
Hadlock and Pierce's (2010) index	-0.276*** (-2.6)	-0.376** (-2.3)	-0.213* (-1.9)
<i>Ln[(Option proceeds + tax benefits)/#employees]</i>	-0.005 (-0.4)	-0.003 (-0.1)	-0.004 (-0.3)
<i>Panel B: Controlling for corporate governance measures (N = 4,647)</i>			
<i>Ln(1+ EmpOpt)</i>	0.060** (2.3)	0.100** (2.5)	0.069** (2.5)
G-index	0.017 (1.3)	0.019 (0.9)	0.011 (0.8)
Board size	-0.024* (-1.7)	-0.040* (-1.8)	-0.029* (-1.9)
Institutional holdings	-0.241 (-1.5)	-0.350 (-1.4)	-0.285* (-1.7)
<i>Panel C: Excluding firms in 'Silicon Valley' and industry clusters (MSA level) (N = 4,286)</i>			
<i>Ln(1+ EmpOpt)</i>	0.062*** (2.7)	0.086** (2.4)	0.063*** (2.7)
<i>Panel D: Controlling for geographic fixed effects (Two-digit ZIP code) (N = 5,640)</i>			
<i>Ln(1+ EmpOpt)</i>	0.067*** (3.0)	0.104*** (3.0)	0.075*** (3.2)
<i>Panel E: Controlling for factors related to reverse causality (N = 5,189)</i>			
<i>Ln(1+ EmpOpt)</i>	0.061*** (2.7)	0.090** (2.5)	0.066*** (2.7)
% of population in the county with college education	-0.003 (-0.8)	-0.003 (-0.4)	-0.002 (-0.4)
Religiosity	-0.225 (-1.0)	-0.539 (-1.6)	-0.275 (-1.2)
Catholic/Protestant	0.167* (1.7)	0.232 (1.5)	0.135 (1.3)
Local median abnormal returns	-0.129 (-1.4)	-0.032 (-0.2)	-0.130 (-1.3)
Local beta	0.020 (1.0)	0.061* (1.8)	0.036 (1.6)

**Table 4: Instrumental variables approach**

The sample consists of firms jointly covered in the IRRC Dilution Database, the ExecuComp, and the NBER Patent and Citation Database between 1998 and 2003. *EmpOpt* is value of non-executive stock options per employee. *ExeOpt* is average value of stock options across the top five executives. *Patents* is the number of patents applied for. *Qcitations* and *Tcitations* are patent citations adjusted using the weighting index of Hall, Jaffe, and Trajtenberg (2001) and the method of time-technology class fixed effect, respectively. *EmpOpt\_Other* is average value of annual grants of non-executive stock option per employee across all zero-citation firms that share the same two-digit ZIP code with the firm but do not belong to the firm's two-digit SIC industry. *Ln(Number of shares)* is the natural logarithm of the number of shares outstanding for the firm. Column (1) reports the estimates of the first-stage regression and columns (2) to (4) report the estimates of the second-stage regressions using the 2SLS model. Other variable definitions are in the legend of Table 2. The *t*-statistics in parentheses are calculated from the Huber/White/Sandwich heteroskedastic consistent errors, which are also corrected for correlation across observations for a given firm. The symbols \*\*\*, \*\*, and \* denote significance at the 1%, 5%, and 10% levels, respectively.

	1st Stage		2nd Stage	
	<i>Ln(1+ EmpOpt)</i>	<i>Ln(1+Patents)</i>	<i>Ln(1+Qcitations)</i>	<i>Ln(1+Tcitations)</i>
	(1)	(2)	(3)	(4)
<i>Ln(1+ EmpOpt)</i>	N/A	0.431*** (2.8)	0.602** (2.6)	0.501*** (3.0)
<i>Ln(1+ EmpOpt_Other)</i>	0.078*** (4.7)	N/A	N/A	N/A
<i>Ln(Number of shares)</i>	0.333*** (6.5)	N/A	N/A	N/A
<i>Ln(1+ ExeOpt)</i>	0.018*** (4.0)	-0.007 (-1.2)	-0.006 (-0.6)	-0.007 (-1.2)
<i>R&amp;D/Assets</i>	3.555*** (7.2)	4.266*** (4.5)	7.311*** (4.8)	3.915*** (3.9)
<i>Ln(Assets)</i>	-0.247*** (-5.3)	0.517*** (17.6)	0.744*** (16.4)	0.527*** (16.8)
<i>Ln(Firm age)</i>	-0.320*** (-9.6)	0.242*** (3.5)	0.328*** (3.2)	0.251*** (3.5)
<i>Ln(PPE/#employees)</i>	0.369*** (11.6)	-0.124 (-1.6)	-0.161 (-1.3)	-0.151* (-1.8)
<i>Ln(Sales/#employees)</i>	0.614*** (13.5)	-0.282*** (-2.7)	-0.388** (-2.4)	-0.328*** (-3.0)
<i>ROA</i>	0.629** (2.1)	0.808*** (2.6)	1.395*** (2.7)	0.725** (2.2)
<i>M/B</i>	0.220*** (14.0)	-0.057 (-1.4)	-0.056 (-0.9)	-0.064 (-1.4)
<i>Sales growth</i>	0.307*** (4.9)	-0.286*** (-4.4)	-0.417*** (-4.0)	-0.309*** (-4.5)
<i>Leverage</i>	-0.310* (-1.9)	-0.313 (-1.4)	-0.553 (-1.6)	-0.317 (-1.3)
<i>Cash/Assets</i>	2.063*** (12.4)	-0.772* (-1.9)	-1.194* (-1.9)	-1.031** (-2.4)
<i>Stock volatility</i>	-3.621* (-1.7)	4.553** (2.1)	8.865** (2.5)	5.774** (2.4)
<i>Stock return</i>	-0.079*** (-2.8)	0.125*** (4.2)	0.230*** (4.3)	0.145*** (4.4)
<i>Herfindahl</i>	-1.779*** (-4.3)	0.852 (1.4)	1.350 (1.4)	0.871 (1.4)
<i>Herfindahl<sup>2</sup></i>	1.962*** (4.0)	-0.553 (-0.8)	-0.702 (-0.7)	-0.503 (-0.7)
Industry and year fixed effects	Y	Y	Y	Y
Joint test of excluded instruments	F(2, 1346) = 36.15 Prob > F = 0.00	N/A	N/A	N/A
<i>J</i> -statistics ( <i>p</i> -value)	N/A	0.88	0.41	0.94
N/R-squared	5,315/0.72	5,315/0.49	5,315/0.47	5,315/0.43

**Table 5: Cross-sectional differences in the effects of employee stock options on innovation**

This table partitions firms into subsamples and re-estimates the regressions in Table 2 for different subsamples. *EmpOpt* is value of non-executive stock options per employee. Other variable definitions are in the legend of Table 2. All regressions include the same control variables as those used in Table 2, but their coefficients are not tabulated. In Panel A, a firm with an employee treatment index equal to (greater than) zero or with R&D per employee below (above) the sample median is classified as having low (high) employee importance. In Panel B, a firm is classified as having high (low) risk of free-riding if the number of employees is above (below) the sample median, or if growth opportunities per employee is below (above) the sample median. In Panel C, a firm is classified as having *targeted* option plans (*Targeted*) if the number of option grants to non-executives (excluding high-level management) over the total shares outstanding exceeds 0.5%, and broad-based plans otherwise. In Panel D, a firm is classified as having long (short) option expiration period if its average stock option expiration period across all option plans is above (below) the sample median. In Panel E, a firm is classified as having low (high) employee stock ownership if the firm has zero (greater than zero) investment in its own stocks in the defined contribution plans. The *t*-statistics in parentheses are calculated from the Huber/White/Sandwich heteroskedastic consistent errors, which are also corrected for correlation across observations for a given firm. The symbols \*\*\*, \*\*, and \* denote significance at the 1%, 5%, and 10% levels, respectively.

	<i>Ln(1+Patents)</i>		<i>Ln(1+Qcitations)</i>		<i>Ln(1+Tcitations)</i>	
<i>Panel A: Partitioning the sample based on importance of employee input</i>						
	Low	High	Low	High	Low	High
<i>Zero vs. positive KLD employee treatment index (<math>N_{Low} = 2,269</math>; <math>N_{High} = 965</math>)</i>						
<i>Ln(1+ EmpOpt)</i>	0.042 (1.3)	0.140** (2.3)	0.051 (1.0)	0.246** (2.6)	0.047 (1.4)	0.160** (2.3)
<i>Partitioning the sample according to per employee R&amp;D expenses (<math>N_{Low} = 2,716</math>; <math>N_{High} = 2,881</math>)</i>						
<i>Ln(1+ EmpOpt)</i>	-0.005 (-0.3)	0.112*** (3.1)	0.005 (0.2)	0.158*** (2.7)	0.001 (0.1)	0.124*** (3.1)
<i>Panel B: Partitioning the sample based on the risk of free-riding</i>						
	High	Low	High	Low	High	Low
<i>Partitioning the sample according to the number of employees (<math>N_{High} = 2,807</math>; <math>N_{Low} = 2,814</math>)</i>						
<i>Ln(1+ EmpOpt)</i>	0.035 (0.9)	0.068*** (2.8)	0.074 (1.3)	0.099** (2.4)	0.049 (1.2)	0.072*** (2.7)
<i>Partitioning the sample according to per-employee growth opportunities (<math>N_{High} = 2,809</math>; <math>N_{Low} = 2,812</math>)</i>						
<i>Ln(1+ EmpOpt)</i>	0.014 (0.5)	0.078** (2.5)	0.035 (0.8)	0.110** (2.3)	0.025 (0.9)	0.079** (2.3)
<i>Panel C: Targeted vs. broad-based option plans (<math>N_{Targeted} = 1,201</math>; <math>N_{Broad-based} = 4,234</math>)</i>						
	Targeted	Broad	Targeted	Broad	Targeted	Broad
<i>Ln(1+ EmpOpt)</i>	-0.002 (-0.1)	0.061** (2.3)	0.011 (0.2)	0.082* (1.9)	0.021 (0.6)	0.059** (2.1)
<i>Panel D: Partitioning the sample according to the average stock option expiration period (<math>N_{Short} = 2,676</math>; <math>N_{Long} = 2,769</math>)</i>						
	Short	Long	Short	Long	Short	Long
<i>Ln(1+ EmpOpt)</i>	0.037 (1.3)	0.079*** (2.6)	0.050 (1.1)	0.133*** (2.7)	0.032 (1.1)	0.098*** (3.0)
<i>Panel E: Positive vs. zero employee stock ownership (<math>N_{High} = 2,264</math>; <math>N_{Low} = 2,022</math>)</i>						
	High	Low	High	Low	High	Low
<i>Ln(1+ EmpOpt)</i>	0.040 (1.2)	0.078** (2.1)	0.052 (1.0)	0.138** (2.4)	0.040 (1.2)	0.090** (2.2)

**Table 6: Effects of non-executive employee stock options on R&D activities**

The sample consists of firms jointly covered in the IRRC Dilution Database, the ExecuComp, and the NBER Patent and Citation Database between 1998 and 2003. Column (1) reports the estimates of OLS regression with  $\ln(1+R\&D/\#employees)$  as the dependent variable. In column (2), the dependent variable is  $R\&D/Assets$ .  $RNDD$  is defined as an indicator that equals one if R&D expenses are missing, and zero otherwise. All other control variables are the same as those used in Table 2. The  $t$ -statistics in parentheses are calculated from the Huber/White/Sandwich heteroskedastic consistent errors, which are also corrected for correlation across observations for a given firm. The symbols \*\*\*, \*\*, and \* denote significance at the 1%, 5%, and 10% levels, respectively.

	<i>R&amp;D intensity</i>	<i>R&amp;D/Assets</i>
	OLS (1)	OLS (2)
<i>Ln(1+ EmpOpt)</i>	0.179*** (12.4)	0.007*** (9.6)
<i>Ln(1+ ExeOpt)</i>	0.007** (2.4)	0.000*** (3.1)
<i>RNDD</i>	-1.387*** (-25.7)	-0.029*** (-14.3)
<i>Ln(Assets)</i>	0.065*** (3.8)	-0.003*** (-2.7)
<i>Ln(Firm age)</i>	0.077*** (3.1)	0.005*** (3.3)
<i>Ln(PPE/#employees)</i>	0.059** (2.1)	0.000 (0.3)
<i>Ln(Sales/#employees)</i>	0.091** (2.3)	-0.002 (-0.9)
<i>ROA</i>	-1.481*** (-6.4)	-0.169*** (-5.1)
<i>M/B</i>	0.026** (2.3)	0.003** (2.0)
<i>Sales growth</i>	-0.148*** (-3.9)	-0.005 (-1.2)
<i>Leverage</i>	-0.483*** (-3.9)	-0.023*** (-2.7)
<i>Cash/Assets</i>	1.800*** (13.1)	0.065*** (6.5)
<i>Stock volatility</i>	9.969*** (6.7)	0.439*** (3.4)
<i>Stock return</i>	0.101*** (6.0)	0.003* (1.8)
<i>Herfindahl</i>	-1.531*** (-5.4)	-0.075*** (-5.9)
<i>Herfindahl</i> <sup>2</sup>	1.760*** (5.6)	0.082*** (6.2)
Industry and year fixed effects	Y	Y
N/R-squared	5,640/0.81	5,640/0.56

**Table 7: Effects of employee incentives on innovation output**

The sample consists of firms jointly covered in the IRRC Dilution Database, the ExecuComp, and the NBER Patent and Citation Database between 1998 and 2003. *EmpDelta* (*EexDelta*) is the average sensitivity of the value of non-executive (top five executives') stock options to a 1% change in stock price. *EmpVega* (*ExeVega*) is the average sensitivity of the value of non-executive's (the top five executives') stock options (stock-based compensation) to a 1% change in stock return volatility. *Patents* is the number of patents applied for. *Qcitations* and *Tcitations* are patent citations adjusted using the weighting index of Hall, Jaffe, and Trajtenberg (2001) and the method of time-technology class fixed effect, respectively. Other variables are defined in the legend of Table 2. The *t*-statistics in parentheses are calculated from the Huber/White/Sandwich heteroskedastic consistent errors, which are also corrected for correlation across observations for a given firm. The symbols \*\*\*, \*\*, and \* denote significance at the 1%, 5%, and 10% levels, respectively.

	<i>Ln(1+Patents)</i>	<i>Ln(1+Qcitations)</i>	<i>Ln(1+Tcitations)</i>
	OLS	OLS	OLS
	(1)	(2)	(3)
<i>Ln(1+ EmpDelta)</i>	0.013 (0.5)	0.019 (0.4)	0.025 (0.8)
<i>Ln(1+ EmpVega)</i>	0.096*** (4.4)	0.154*** (4.2)	0.091*** (3.9)
<i>Ln(1+ ExeDelta)</i>	-0.000 (-0.0)	-0.006 (-0.5)	0.000 (0.0)
<i>Ln(1+ ExeVega)</i>	0.007 (0.9)	0.017 (1.5)	0.008 (1.1)
<i>R&amp;D/Assets</i>	5.599*** (8.1)	9.029*** (7.7)	5.489*** (7.4)
<i>Ln(Assets)</i>	0.525*** (18.6)	0.758*** (17.2)	0.534*** (17.9)
<i>Ln(Firm age)</i>	0.118*** (2.7)	0.158** (2.4)	0.108** (2.4)
<i>Ln(PPE/#employees)</i>	-0.002 (-0.0)	0.009 (0.1)	-0.001 (-0.0)
<i>Ln(Sales/#employees)</i>	-0.098** (-2.0)	-0.145* (-1.9)	-0.108** (-2.1)
<i>ROA</i>	1.085*** (4.2)	1.754*** (4.0)	1.042*** (3.7)
<i>M/B</i>	0.045*** (3.2)	0.087*** (3.5)	0.054*** (3.4)
<i>Sales growth</i>	-0.184*** (-4.0)	-0.270*** (-3.4)	-0.188*** (-3.9)
<i>Leverage</i>	-0.524*** (-2.7)	-0.844*** (-2.7)	-0.550*** (-2.7)
<i>Cash/Assets</i>	0.010 (0.0)	-0.133 (-0.4)	-0.123 (-0.5)
<i>Stock volatility</i>	4.070** (2.1)	8.181** (2.6)	5.402** (2.6)
<i>Stock return</i>	0.105*** (4.1)	0.211*** (4.4)	0.128*** (4.4)
<i>Herfindahl</i>	0.077 (0.2)	0.264 (0.4)	-0.024 (-0.0)
<i>Herfindahl</i> <sup>2</sup>	0.276 (0.5)	0.468 (0.6)	0.452 (0.8)
Industry and year fixed effects	Y	Y	Y
N/R-squared	5,640/0.55	5,640/0.51	5,640/0.50