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Impede Corporate Innovation?

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Abstract

We examine the impacts of accounting conservatism on corporate innovation. We find that firms with a greater degree of accounting conservatism generate fewer patents and patent citations. They engage less in R&D activities but our results hold after controlling for this lower activity. Moreover, the cash-flows generated by the innovations in firms with more conservative accounting have shorter horizons. The negative effects of accounting conservatism are more pronounced when firms' need for innovation is higher, when the principal is less informed about the behavior of the managers, when the product development cycle is longer, when managers face higher pay sensitivity to accounting performance, or when managers have shorter investment horizons or are under heavier pressure from short-term institutional investors.

I. INTRODUCTION

Holmstrom (1989) argues that innovation projects are: (a) risky - there is a high probability of failure, but also prospects for extraordinary returns; (b) unpredictable - many future contingencies are impossible to foresee; (c) long-term and multi-stage - the project has an invention, a development and a completion stage, and can be terminated between those; (d) idiosyncratic - not easily comparable to other projects; (e) labor intensive. These characteristics make the oversight of innovation projects difficult in a standard framework. For example, Holmstrom (1989) argues that the conventional pay-for-performance system is not effective in encouraging innovations. He argues that performance measures for innovative activities are noisier, and therefore to motivate innovation the principal should rely on compensation schemes that are less sensitive to performance. Manso (2011) makes a similar point by showing analytically that standard pay-for-performance schemes that punish failures with low rewards and termination may in fact have adverse effects on innovation. More importantly, he demonstrates that the optimal innovation-motivating incentive scheme should exhibit substantial tolerance (or even reward) for early failure and reward for long-term success.¹

We examine how accounting conservatism influences corporate innovation through the monitoring of managers.² The principle of accounting conservatism is to recognize losses as they become probable but delay the recognition of profits until there is a legal claim to the revenues generating them and that the revenues are verifiable. This accounting practice can help mitigate problems caused by moral hazard. For example, Watts (2003) and Francis and Martin (2010) show that accounting conservatism can serve as an important governance mechanism that

¹ Ferreira, Manso, and Silva (2012) also analytically show that tolerance of failure in the short run is necessary for nurturing innovation.

² Accounting conservatism in this study refers to the timeliness of loss recognition rather than the accounting treatment of R&D expenditures.

deters managers from undertaking negative net present value (NPV) projects by accelerating future investment losses into current earnings. This accounting principle is particularly suitable for debtholders who are subject to a large downside risk but receive none of the upside potential. However, shareholders, particularly those of R&D intensive firms, are protected on the downside by the limited liability rule but enjoy the full upside. Thus, shareholders in firms with high upside potential should prefer avoiding mechanisms that hinder innovations and accounting conservatism may be one of them. For example, Roychowdhury (2010) conjectures that accounting conservatism may discourage managers from making risky investment because of the increased likelihood of an economic loss occurring. Consistent with this view, Kravet (2012) shows that accounting conservatism causes managers to avoid making risky acquisitions with positive NPV, implying the possibility of a dysfunctional effect of accounting conservatism. This tendency should be exacerbated for innovative projects because of their highly risky, long-term, and unpredictable nature. We therefore expect that firms subject to a greater degree of accounting conservatism should engage less in innovative projects with uncertain and delayed but potentially large pay-offs. This negative effect of accounting conservatism on innovation should be exacerbated for firms in which managers face higher performance pressure or are under heavier pressure from short-term institutional investors but should be less pronounced for those in which shareholders and managers have a long investment horizon or those in which the tolerance for short-term accounting losses is high.

Our empirical findings are consistent with these expectations. Using a large panel of US firms covered by the NBER Patent and Citation Database over the 1976-2003 period, we document that accounting conservatism hinders corporate innovation. Specifically, accounting conservatism is negatively associated with the quantity and quality of innovation, which are

measured by the number of patents and the number of patent citations, respectively. Firms with a greater degree of accounting conservatism also engage less in R&D activities but our results hold after controlling for this lower activity. Moreover, the cash-flows generated by innovations have shorter horizons in firms with more conservative accounting. We also find that the negative effects of accounting conservatism on innovation are more pronounced 1) when firms' need for innovation is higher (i.e., firms operating in innovative industries or firms whose stocks displaying a lottery-like feature), 2) when the principal is less informed about the behavior of the managers, 3) when managers face higher performance pressure (i.e., CEO compensation is more strongly tied to accounting performance), 4) when the product development cycle is longer, or 5) when managers' or shareholders' investment horizon is shorter (i.e., the distance to CEO retirement is shorter or short-term institutional ownership is larger). These results are both economically and statistically significant, and hold for several alternative measures of accounting conservatism, including those proposed by Ahmed and Duellman (2007), Ball and Shivakumar (2006), Basu (1997), , Givoly and Hayn (2000), and Khan and Watts' (2009).

We contribute to the literature by considering how accounting properties can affect investment decisions, particularly those related to intangible assets. Prior research such as Biddle and Hilary (2006) and Biddle, Hilary, and Verdi (2009) shows that good reporting quality improves the investment process. Prior literature also suggests that accounting conservatism can be an important governance mechanism that deters managers from undertaking negative NPV projects by accelerating future investment losses into current earnings (e.g., Watts (2003), Francis and Martin (2010)). We extend this literature by showing that a reporting property that is often desirable can also have a negative effect on the investment quality by setting perverse

incentives for managers, particularly for firms that are subject to high short-term performance pressure and those that rely heavily on innovation.

The remainder of the paper proceeds as follows. We develop our main hypothesis in Section II. We discuss our empirical design and sample in Section III. We discuss our main empirical results in Section IV and some additional results in Section V. We summarize and conclude in Section VI.

II. HYPOTHESIS DEVELOPMENT

Manso (2011, p.1823) notes that “motivating innovation is important in many incentives problems.” However, doing so presents unique challenges. In a standard principal-agent framework, a principal supplies capital to a manager who is entrusted with its management. This setting creates a potential moral hazard problem in which the manager tries to either shirk or engage in negative NPV projects that maximize her own utility at the expense of the principal’s welfare. A standard solution to this problem is to offer a compensation contract to the manager that links pay and performance in a way that punishes failures with penalty including termination. Under this incentive scheme, compensation depends not only on the total performance, but also on the path of the performance: a manager who performs well initially but poorly later typically earns more than a manager who performs poorly initially but well later. This incentive scheme encourages risk-averse managers to use established procedures at the expense of new and innovative approaches that are likely to fail but have the potential to deliver huge success at a later stage. In essence, investors who want to foster the pursuit of these projects need to remove the threat of short-term penalty while keeping long-term incentives.

Prior empirical results are generally consistent with these views. For example, Chemmanur and Tian (2011) find that firms with a larger number of antitakeover provisions (ATPs) are more innovative, and that this positive impact of ATPs on innovation contributes positively to overall firm value. Acharya, Subramanian, and Bghai (2010) find that wrongful discharge laws that make it costly for firms to arbitrarily discharge employees foster innovation. Francis, Hasan, and Sharma (2011) find that long-term CEO incentive plans in the form of options are positively related to patents and citations to patents since the convexity of options has a positive effect on innovation. However, they find no relation between pay-performance sensitivity and innovation. They also find that golden parachutes that provide protections to managers who suffer from job loss are associated with better innovation. Chang et al. (2012) document that stock options to rank-and-file employees enhance employees' risk-taking incentives and failure-bearing capacities in high risk-profile innovative activities, and thus improve innovation outcomes. Lerner and Wulf (2007) find that more long-term incentives are associated with more heavily cited patents, more frequent awards, and patents of greater originality. Bushee (1998) finds that concentrated ownership by institutions that have high portfolio turnover and engage in momentum trading significantly increases the probability that managers reduce spending on R&D activities to reverse an earnings decline.

Financial reporting and accounting oversight can play a significant role in fostering or discouraging innovation by affecting the moral hazard problem: weak monitoring encourages shirking and sub-optimal investment while excessive short-term performance pressure discourages innovation and fosters myopic behavior. For example, Biddle, Hilary, and Verdi (2009) show that firms with poor quality reporting are more likely to invest sub-optimally in R&D. However, Cheng, Subramanyam, and Zhang (2005) find that firms that offer more

frequent earnings guidance spend less on R&D and meet analyst consensus more frequently. They conclude that these results are consistent with more frequent earnings guidance being associated with myopic R&D spending. He and Tian (2011) document that firms covered by a larger number of analysts generate not only fewer patents but also patents with smaller impact.

We focus on a specific dimension of accounting oversight, namely, conservatism. Naturally, we observe a similar trade-off between hindering innovation with strong monitoring and encouraging moral hazard with weak monitoring when we do so. Watts (2003) and Francis and Martin (2010) indicate that accounting conservatism serves as an important governance mechanism in deterring managers from undertaking negative NPV projects. However, accounting conservatism is geared to a large extent toward satisfying the needs of creditors (Watts (2003), LaFond and Watts (2008), LaFond and Roychowdhury (2008)). It typically involves curbing “excessive” risk but this “excessive” level is considered from the creditor’s point-of-view. For example, Ma (2010) finds that accounting conservatism reduces corporate investments and future operating performance for financially constrained firms and argues that accounting conservatism can cause dysfunctional investment incentives for managers and motivate them to forego positive NPV projects. Kravet (2012) posits that the constraint of investment in risky positive NPV projects represents a cost of conservative accounting.

We use this line of research to develop our main hypothesis that accounting conservatism curbs innovation but through a channel that is not directly related to liquidity constraints. Specifically, we start with the premise that any substantial innovative project will take multiple years before delivering positive results (e.g., Holmstrom (1989)). A sufficiently patient or well-informed principal may be ready to suspend judgment in the earlier periods. Knowing this, a manager who is sufficiently compensated for taking risk may decide to invest in projects with

large albeit uncertain pay-offs. To the extent that a share is seen as a call option on a firm's future cash-flows, investing in such projects may be valuable for a shareholder. However, if the reporting and incentive system is such that it puts pressure on the manager to deliver not only a large pay-off in the later part of the cycle but also a minimum return in the early stages, managers should avoid investing in such projects and, to the extent that they have to invest in R&D, choose safer and less innovative projects with shorter horizons. Consistent with this view, Graham, Harvey, and Rajgopal (2005) report that 78% of the executives in their survey admit that the accounting effect of an investment would affect their decision to engage in that investment. A majority of CFOs in the survey also declare that they are willing to sacrifice long-term firm value to meet their desired short-term earnings targets. In particular, 80% of survey participants report that they would decrease R&D as well as other discretionary expenditure to meet an earnings target. In other words, a manager may decide (*ex post*) to cut R&D expenses to avoid reporting a loss, even if this means forgoing the benefit of the R&D expenses that have been previously incurred. Such decision would be economically costly but would improve reported earnings, at least in the short run. Realizing this possibility, managers may decide (*ex ante*) to avoid multi-stage innovative research projects. Accounting conservatism may exacerbate this pressure by fostering the early recognition of losses and thus make it difficult to distinguish between bad (i.e., negative NPV) projects and innovative projects that have potentially large but uncertain and delayed pay-offs. Realizing this problem, managers may avoid such projects. Thus, accounting conservatism can increase the pressure on managers to meet short-term earnings targets, reduce the tolerance for early failures, and give rise to managerial short-termism in certain cases. These arguments suggest that firms with conservative

accounting should be less innovative than firms with “liberal” accounting and motivate our main hypothesis:

H: Firms with a greater degree of accounting conservatism generate a lower level of innovation than firms with a lower degree of accounting conservatism.

It should be noted that in our hypothesis, the channel through which accounting conservatism affects innovation is not a firm’s financial constraint. It is rather through the principal’s unwillingness to wait until the end of the project to reward or punish the manager. We thus expect that our hypothesized effect is more pronounced when the principal is less informed about the behavior of the managers, when short-term accounting pressure is greater, when the product development cycle is longer, or when managers’ or shareholders’ investment horizon is shorter. We discuss these testable predictions in greater detail in Section V.

III. EMPIRICAL DESIGN, SAMPLE, AND SUMMARY STATISTICS

Empirical Design

To test our main hypothesis, we estimate the following model:

$$Innov_{i,t} = \alpha + \beta Cons_{i,t-1} + \gamma Controls_{i,t-1} + Year_t + Industry_{i,t} + \varepsilon_{i,t} \quad (1)$$

Innov represents our measures of innovation. We consider two measures of *Innov*: (1) the log of one plus the number of patents registered by firm *i* in year *t*, $(\ln(1+Patent))^3$ and (2) the

³ Our results do not change qualitatively if we use the “time-technology class fixed effect” method to adjust for the difference in patenting practices across different technological fields (Atanassov (2012), Hirshleifer, Low, and Teoh (2012)). This method scales the number of patents by the average number of patents issued in a certain year by all firms for a given class of technology.

log of one plus the number of patent citations.⁴ The number of citations is calculated over the entire life of the patent. However, calculating citations in this way can create truncation bias since our database coverage ends in 2006 and does not include citations after this year. This truncation bias is naturally more severe for more recent patents since they have less time to accumulate citations than patents created in earlier years. To deal with this issue, we use the “weighting index” method suggested by Hall, Jaffe, and Trajtenberg (2001) as well as the “time-technology class fixed effect” method employed by Atanassov (2012) and Hirshleifer, Low, and Teoh (2012). The first method adjusts each patent’s raw citation count by multiplying the weighting index calculated by Hall, Jaffe, and Trajtenberg (2001, 2005), while the second method scales the citations by the average number of citations for all patent issues in the same technology class in the year. The resulting measures are denoted as $Ln(1+Qcitation)$ and $Ln(1+TTcitation)$, respectively.

Cons represents our key explanatory variable of interest, accounting conservatism. Initially, we use Khan and Watts’ (2009) measure of accounting conservatism C_Score as our treatment variable but as shown in Section IV, our results are robust to using alternative measures of accounting conservatism. Specifically, C_Score is constructed based on Basu’s (1998) model as follows.

$$X_i = \beta_1 + \beta_2 D_i + \beta_3 R_i + \beta_4 D_i R_i + e_i, \quad (2)$$

where X is earnings over the market value of equity at the prior fiscal year end, R is the annual stock return, D is a dummy variable that is equal to one if $R < 0$ and zero otherwise. β_4 measures the incremental timeliness for bad news over good news, namely, accounting conservatism.

⁴ We do not exclude self-citations in the baseline regressions since Hall, Jaffe, and Trajtenberg (2005) find that self-citations are more valuable than external citations. They suggest that self-citations, which require generating further related patents, are indicative of the firm’s competitive advantage in the relevant technology and thus should be more important than other citations. Our results do not change if we exclude self-citations.

Khan and Watts (2009) assume that both β_3 and β_4 are linear functions of firm-specific characteristics each year.

$$\begin{aligned}\beta_3 &= \mu_1 + \mu_2 \text{Ln}(E)_i + \mu_3 MB_i + \mu_4 Lev_i \\ \beta_4 &= C_Score = \lambda_1 + \lambda_2 \text{Ln}(E)_i + \lambda_3 MB_i + \lambda_4 Lev_i,\end{aligned}\tag{3}$$

where $\text{Ln}(E)$ is the log of the market value of equity, MB is the ratio of market value of equity to book value of equity, and Lev is total debt divided by the market value of equity. Thus, the annual cross-sectional regression model used to estimate C_Score can be written as

$$\begin{aligned}X_i &= \beta_1 + \beta_2 D_i + R_i(\mu_1 + \mu_2 \text{Ln}(E)_i + \mu_3 MB_i + \mu_4 Lev_i) + D_i R_i(\lambda_1 + \lambda_2 \text{Ln}(E)_i + \lambda_3 MB_i + \lambda_4 Lev_i) \\ &\quad + (\delta_1 \text{Ln}(E)_i + \delta_2 MB_i + \delta_3 Lev_i + \delta_4 D_i \text{Ln}(E)_i + \delta_5 D_i MB_i + \delta_6 D_i Lev_i) + \varepsilon_i,\end{aligned}\tag{4}$$

where coefficients δ_1 - δ_6 capture the independent effects of firm specific variables and their interactions with D on earnings, while coefficients λ_1 - λ_4 are used to construct C_Score .

Controls in equation (1) represents a vector of control variables. Specifically, we control for the R&D effort by including R&D expenses over total assets ($R\&D/Assets$).⁵ We control for firm size measured as the log of total assets,⁶ firm age, and capital intensity measured as the log of property, plant, and equipment divided by the number of employees ($\text{Ln}(PPE/\#Employees)$) since Hall and Ziedonis (2001) argue that large, mature, and capital-intensive firms are associated with more patents and citations. Following Hirshleifer, Low, and Teoh (2012), we also include leverage, liquidity, MB , sales growth, and profitability (ROA). Since Hirshleifer, Low, and Teoh (2011) find that high innovation productivity is associated with better stock performance, we include the compounded monthly stock returns over the fiscal year (*Stock return*). Chan, Lakonishok, and Sougiannis (2001) show that R&D intensive firms are

⁵ Following prior literature (e.g., Chemmanur and Tian (2011), Hirshleifer, Low, and Teoh (2012)), missing R&D expenses are treated as zero. Our results are qualitatively the same if we include in regressions an R&D indicator that equals one if R&D expenses are missing and zero otherwise.

⁶ Using total sales, the market value of equity, or the total number of employees as alternative proxies for firm size does not affect our results.

associated with higher stock return volatility. Therefore, we include the standard deviation of monthly stock return over the past fiscal year (*Stock volatility*) as an additional control variable. Since He and Tian (2011) document that analyst coverage has a negative impact on innovation, we also control for analyst coverage using the number of analysts making earning forecast in a given year. Finally, Aghion et al. (2005) document an inverted-U relationship between product market competition and innovation. Accordingly, following Atanasov (2008) and Chemmanur and Tian (2011), we include the Herfindahl index calculated at the three-digit SIC (*Herfindahl*) and its square term ($Herfindahl^2$) in the regressions. Appendix A provides a detailed description of the construction of these variables. We also include year and two-digit SIC industry fixed effects in our specifications. 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.

Sample

We obtain information on patents from the NBER Patent and Citation Database. This database was developed by Hall, Jaffe, and Trajtenberg (2001) and contains detailed information on all U.S. patents granted by the U.S. Patent and Trademark Office (USPTO) from 1976 to 2006. According to Hall, Jaffe, and Trajtenberg (2001), the average length between the day the patent is filed and the day the patent is granted is approximately two years. Since the NBER Patent and Citation Database only covers patents granted, the coverage of the patents filed in 2004 and 2005 is partial. Thus, to minimize the potential effect of truncation bias, we follow Hall, Jaffe, and Trajtenberg (2001) and stop our sample period in 2003. We obtain accounting data from the Compustat database and stock price and return data from the CRSP database.

Following previous studies, we use the application year to merge the Compustat and the NBER Patent and Citation databases since the grant year is likely to be distant from the actual planning of the R&D associated with the patent (Griliches, Pakes, and Hall (1988), Hirshleifer, Low, and Teoh (2012), Atanassov (2012)). We then exclude firms in financial (SIC codes 6000-6999) and utility (SIC codes 4900-4999) industries from the sample (Atanassov (2012), Tian and Wang (2012), Hirshleifer, Low, and Teoh (2012)). Also excluded are firms operating in industries without any registered patents in any year in the entire NBER Patent and Citation Database. These restrictions result in a final sample of 70,871 firm-year observations.

Summary Statistics

Table 1 presents summary statistics for variables used in the regression analyses.

Table I Summary Statistics

Panel A indicates that, on average, firms in our sample register slightly less than 6 patents per year but the median is zero. The skewness also exists when we consider the number of citations. The average number of citations across all firms in our sample is greater than 107, while the median is zero. To mitigate this skewness, we use the log of these variables in the regression analyses. In Panel B, we split the sample according to the value of C_Score . Results indicate that the number of patents and patent citations increase monotonically as C_Score decreases. For example, the mean number of patents in the most conservative group is close to zero but approaches 20 in the least conservative group. Similarly, as we move from the most conservative group to the least conservative group, the mean number of citations increases from

about 8 to 420. The results using *Qcitation* and *TTcitation* are similar. In all cases, the difference between the two extreme quintiles is statistically significant with a p -value below 0.01. These preliminary results are consistent with our main hypothesis. Panel C presents descriptive statistics for variables used in regressions.

Table 2 reports the correlations among *C_Score*, innovation measures, and control variables.

Table II Pearson Correlation Matrix

Most pair-wise correlations are significantly different from zero at the 1% level. As expected, our three measures of innovations, ($\ln(1+Patent)$, $\ln(1+Qcitation)$, and $\ln(1+TTcitation)$), are highly correlated with each other. Consistent with our hypothesis, *C_Score* is negatively correlated with all three measures of innovations (correlation coefficients of approximately -0.3). The correlation between *C_Score* and R&D intensity is positive but its magnitude is relatively small at 0.044. In addition, as discussed below, we observe an opposite relation once we control for other firm characteristics such as firm size and performance. Not surprisingly, R&D intensity is positively correlated with our measures of innovation but the relation is relatively modest (correlation coefficients of approximately 0.15). The correlations between the control variables are reasonably low in most cases, although in a few cases, they are close to 0.5 (in absolute value). We verify below that multicollinearity is not an issue in our tests.

IV. EMPIRICAL RESULTS

In this section, we examine the effect of accounting conservatism on the quantity and quality of firm innovation activity using the multivariate regression analysis in which the dependent variable is $\ln(1+Patent)$, $\ln(1+Qcitation)$, or $\ln(1+TTcitation)$.

Main Results

We present our main results in Table 3.

Table III Effect of C_Score on Innovation Outputs

We find that C_Score is negatively and significantly related to all three measures of innovations, $\ln(1+Patent)$, $\ln(1+Qcitation)$, and $\ln(1+TTcitation)$ with t -statistics of 5.6, 6.6, and 6.9, respectively. In untabulated tests, we find that the results remain significant if we cluster observations by firm and year with t -statistics of 3.7, 4.4, and 4.4, respectively. Increasing C_Score from the 1st quartile (0.04) to the 3rd quartile (0.17) decreases the values of $Patent$, $Qcitation$, and $TTcitation$ by 5%, 9%, and 6% from their respective means.⁷ The mean Variance Inflation Factor (VIF) is below 2, suggesting that multicollinearity is not an issue in our setting.

Turning to the control variables, we find that most of their coefficients have the expected signs. For example, firms that engage in more R&D activity innovate more. Firms with more resources (high liquidity and high ROA), higher market to book ratio, or greater stock volatility

⁷ For instance, to calculate the effect of C_Score on the change in the number of patents from its mean value, we first multiply the change of C_Score from the 1st quartile (0.04) to the 3rd quartile (0.17) by the coefficient on C_Score (-0.318), and then by the mean number of patents (5.71) plus one. It is so because $d\ln(1+y)/dx = (dy/dx)/(1+y)$. An increase in C_Score from the 1st quartile to the 3rd quartile can be translated into a 0.28 decrease in the number of patents. Given that the average number of patents is 5.71, a decrease of 0.28 patents represents a 5% decrease from the mean value.

are also more innovative. However, unlike He and Tian (2011), we find that analyst coverage has a positive effect on the number of patents and citations. In untabulated tests, we are able to replicate their results if we use their sample period (1993-2005) instead of ours (1976-2003).

Robustness Checks: Alternative Model Specifications and Endogeneity Tests

Our results are robust to a host of specification checks (untabulated). First, we find even stronger results if we remove R&D intensity from the regression or if we add a binary variable to indicate the absence of R&D information.

Second, our results hold if we control for financial constraints using either Kaplan and Zingales (1997) index, Whited and Wu (2006) index, or Hadlock and Pierce (2010) index, for firm diversification using the log of the number of business segments, for governance quality using either Gompers, Ishii, and Metrick's (2003) *G-index*, board size, the percentage of independent directors, or the percentage of institutional ownership,⁸ for CEO pay-performance-sensitivity (*delta*) and risk-taking incentives (*vega*), for CEO overconfidence using option-based overconfidence measure of Hirshleifer, Low, and Teoh (2012), for industry unionization rate of Hirsch and Macpherson (2003), and for the timeliness of good news using Khan and Watts's (2009) *G_Score*.⁹

Third, our results hold if we exclude the self-citations, firms with zero patents, firms with zero citations, firms engaged in M&As in the prior two years, firms with acquired R&D,¹⁰ firms

⁸ We obtain data on institutional ownership from the Thomson Reuters Institutional (13F) Holdings Database.

⁹ *G_Score* is β_3 in equation (3). We find that the coefficient on *G_Score* is negative when it is included in our regressions, consistent with the argument of Manso (2011) that rewarding short-term success may hurt the incentive to innovate.

¹⁰ *Acquired R&D* is an indicator that takes the value of one if the Compustat R&D footnote indicates "BW" and zero otherwise.

with software development cost, the tech bubble (1998-2000) period, or the post-SOX (2002-2003) period.

Fourth, our results are robust to using alternative measures of accounting conservatism such as a modified version of the *C_Score* (*C_Score* estimated by adding tax-adjusted R&D expenses back),¹¹ Basu (1997) measure, Ball and Shivakumar (2006) measure, and the negative non-operating accruals (Givoly and Hayn (2000), Ahmed and Duellman (2007)).¹²

Fifth, our results are robust if we use the raw innovation measures (instead of using the log values) together with a negative binomial estimation procedure (instead of an OLS estimation) or the average number of citations per patent as the dependent variable.

Finally, our results are robust to controlling for endogeneity bias. For example, to control for potential endogeneity bias caused by omitted unobservable firm characteristics, we include firm-fixed effects in the regressions and find that the *t*-statistics for *C_Score* in regressions (1), (2), and (3) of Table III are -2.0, -3.2, and -3.3, respectively. Although it is not immediately obvious why firm innovation would cause the firm to adopt a conservative accounting policy, especially after controlling for the spending on R&D activity in our specifications, we alleviate the reverse causality concern by lagging the independent variables (including *C_Score*) up to four periods. Our results are unaffected. Next, we include values of our innovation measures (*Innov*) lagged either 3 or 4 periods as additional controls. Our results are unaffected either. We also note that the use of the *C_Score* as a proxy for conservatism mitigates this issue. This variable is essentially a fitted value based on the firm value of $\ln(E)$, *MB*, and *Lev*. If the coefficients used

¹¹ Ma (2010) argues that “Firms with high R&D will have relatively lower earnings as R&D are expensed. In contrast, firms with high R&D enjoy higher stock returns because capital market rationally price in the future benefits of R&D expenditures. Hence, high R&D expenditures can cause a negative relation between earnings and return and affect the measure of conditional accounting conservatism.” Hence, we add R&D expenses back to earnings in the construction of *C_Score*.

¹² These alternative measures of conservatism are defined in Appendix A.

in equation (3) are estimated correctly, then, in essence, we have already instrumented conservatism and the effect of *Innov* on conservatism has been purged. To further increase the confidence that it is indeed the case, we perform several additional robustness tests. First, we note that *Ln(PPE/Employees)*, *Sales growth*, and *Herfindahl index* are statistically insignificant in Table 3. We add these variables in equation (4) as potential quasi-instruments for conservatism. We find that they are statistically significant (the relevant *t*-statistics for pooled regressions are 3.5, -3.5, and -4.5, respectively; *F*-test indicates that the three variables are jointly significant with *p*-value of less than 0.01). We then use this alternative version of *C_Score* based on six variables and find that our results in equation (1) are qualitatively similar. Second, we estimate equation (4) using our baseline model but only for firms in non-innovative industries (i.e., industries for which the level of *Qcitation* is below the sample median each year) where accounting conservatism is less likely to be driven by innovation. We then estimate equation (3) for the entire sample based on the revised coefficients. Our results in equation (1) are qualitatively similar. Third, we reestimate *C_Score* as well as the Basu's (1997) metrics at the industry level.¹³ Again, our results are qualitatively similar. Finally, as an alternative test, we use the enactment of the SEC's Staff Accounting Bulletin (SAB) No. 101 in 1999 as an exogenous shock to the increase in a firm's accounting conservatism. The prior literature documents that SAB 101 reduces the timeliness of revenue recognition, resulting in an exogenous increase in accounting conservatism for a broad cross-section of listed firms (Crawford, Price, and Rountree (2010)).¹⁴ Therefore, the enactment of the SAB 101 can serve as a good experimental setting to examine the effect of accounting conservatism on innovation. Specifically, we replace *C_Score* in equation (1) with the *SAB 101 indicator* (a binary variable

¹³ Specifically, we reestimate *C_Score* and β_4 in equation (2) each year for each 2-digit SIC industry, among which we drop industries with no more than five firms.

¹⁴ We find that the correlation coefficient between *SAB 101 indicator* and *C_Score* is 0.24 in our sample.

that takes the value of one after the enactment of SAB 101 and zero otherwise) and drop the year dummies from equation (1) while keeping other variables including firm-fixed effects. This specification aims to capture the within firm variation in innovation around the enactment of the SEC's SAB 101. We find that the *SAB 101 indicator* is negatively and significantly related to $\ln(1+Patent)$, $\ln(1+Qcitation)$, and $\ln(1+TTcitation)$ with t -statistics of -3.5, -16.1, and -7.6, respectively, suggesting that a positive shock to accounting conservatism causes firms to be less innovative.

V. CROSS-SECTIONAL HETEROGENEITY IN RESULTS

To further examine the validity of our main hypothesis, in this section, we conduct a battery of additional tests.

Properties of Research Projects

First, we examine whether the degree of conservatism affects the properties of the research projects.

Table IV Effect of C_Score on Innovation Horizon

We first consider the horizon of the innovative activities. As discussed in the hypothesis development section, we expect firms with conservative accounting to engage in R&D projects that deliver outcomes faster. To examine this prediction, we follow Hilary and Hui (2012) and regress operating cash-flows in year $t+1$ ($t+3$, $t+5$) on the number of patents and citations, controlling for R&D intensity in period $t-1$, *Size*, *MB*, leverage, beta, and industry indicators.

We estimate the regression separately for firms with high and low C_Score (using the sample median as a cut-off point). Results are reported in Table IV. For the sake of brevity, the regression estimates for control variables are not reported. As shown in Panels A, B, and C, we find that the coefficient estimates on $Ln(1+Patent)$, $Ln(1+Qcitation)$, and $Ln(1+TTcitation)$ for the low C_Score subsample increase as the horizon increases, while the corresponding coefficient estimates for the high C_Score subsample decrease or remain constant.¹⁵ The increase in the magnitude of the coefficients in the low C_Score group is statistically significant (with p -values of 0.09, 0.05, and 0.03, respectively) but not in the high C_Score one. Thus, firms with more conservative accounting not only generate fewer patents and citations, but also, after controlling for the “productivity” of the innovation process, as measured by the number of patents and citations, have lower cash-flows from innovation in the more distant future. While not reported, the results for the coefficient estimates on control variables are similar to those reported by Hilary and Hui (2012).

We then turn our attention to the presence of lottery-like features of a firm’s innovation. Firms could engage in either marginal innovations or “ground-breaking” innovations that are highly uncertain but potentially capable of generating huge returns. We expect that accounting conservatism impedes the second type of innovation more than the first type. To investigate this possibility, we construct a measure of lottery-type firms following the steps similar to the one proposed by Kumar (2009). Specifically, we form a binary variable (*Lottery*) that equals one if the stock price exhibits both above-median idiosyncratic volatilities and above-median idiosyncratic skewness and zero otherwise. We then partition the sample according to the sample median of C_Score and using a probit model, separately regress *Lottery* on each of our

¹⁵ We find, however, that the coefficient estimate on $Ln(1+TTcitation)$ for the high C_Score subsample reverse a bit in year $t+5$.

three measures of innovation ($\ln(1+Patent)$, $\ln(1+Qcitation)$, and $\ln(1+TTcitation)$) controlling for the variables used in equation (1).

Table V Effect of C_Score on Lottery-like Feature of Innovation

Results are presented in Table V. We find that the coefficient estimates on our three measures of innovation are always statistically different across the two subsamples with a p -value of 0.01 or lower in each of the three specifications. The coefficient estimates are negative and significant for firms in the high C_Score subsample, suggesting that innovation in these firms is associated with a lower likelihood of exhibiting lottery-like features. Thus, the adverse effect of accounting conservatism on innovations is particularly severe when innovations generate high uncertainty but greater upside potentials. On the other hand, the coefficient estimates are positive (but insignificant) for firms in the low C_Score subsample.

To further show that accounting conservatism has a more debilitating effect on innovation when firms have greater need for innovation, we divide our sample into firms operating in innovative and non-innovative industries according to whether the average citations per patent ($Qcitation$) is above the sample median average citation across all industries (using a two-digit SIC industry) for a given year. We then reestimate equation (1) by adding an indicator that takes the value of one if the industry is innovative and zero otherwise and its interaction with C_Score . Untabulated results show that the coefficient estimate on the interaction term is negative and significant with t -statistics ranging from 4.7 to 5.3. These results further confirm that accounting conservatism has a most debilitating effect on innovation when innovation is particularly important.

Manager, Shareholder, and Other Firm-specific Characteristics

Next, to better understand the channels through which accounting conservatism affects corporate innovation, we examine whether our results vary across manager, shareholder, and other firm-specific characteristics. As discussed in Section I, we expect the results reported in Table III to be more pronounced when the shareholders are less informed about the behavior of the managers, when the accounting performance pressure is greater, when the product development cycle is longer, or when managers' or shareholders' investment horizon is shorter.

To measure the degree of shareholders' informativeness, we use the dispersion of analyst forecast, measured as the standard deviation of long-term growth analyst forecasts scaled by the mean forecast (Moeller, Schlingemann, and Stulz (2007)). We expect that the pressure on managers to report strong performance is higher when a firm's future uncertainty is greater. For example, Stein (1988) argues that investors are more likely to undervalue firms with a higher degree of information asymmetry and these firms have a greater exposure to hostile takeovers. Hence, managers in these firms should have strong incentives to concentrate on projects that offer quicker and more certain returns rather than invest in innovative projects.

To measure the extent of accounting performance pressure on managers, we use CEO pay-accounting-performance sensitivity. Following Leone, Wu, and Zimmerman (2006), we first estimate the sensitivity of CEO pay to accounting performance over the 1992-1997 period by conducting firm-level time-series regression. We then create an indicator to denote a high or low sensitivity of CEO pay to accounting performance (*PAPS*) using the top and bottom 30th

percentile of the sample as cut-off points and interact it with *C_Score* over the 1998-2003 period.¹⁶

To measure the length of product development cycle, we employ the industry level R&D amortizable life, which reflects the commercial life of the products that emerge from R&D.¹⁷ We classify the industries into three categories: those with an amortizable life shorter than 5 years, those with a life of 5 years, and those with a life longer than 5 years. We then interact *C_Score* with the last two indicators associated with an amortizable life of at least 5 years and include these interaction terms as additional explanatory variables in equation (1).

Finally, we measure managers' and shareholders' investment horizon using the distance to CEO retirement age and short-term institutional ownership, respectively. Following Yim (2012), the distance to CEO retirement age is measured by three indicators for different CEO age groups: 1) young or mid age CEOs (younger than 59); 2) old CEOs (between ages of 59 and 65), and 3) CEOs whose age exceeds the statutory retirement age of 65. We then include *C_Score*, the first two indicators, their interaction terms, and CEO tenure in equation (1) and reestimate it. To measure a firm's short-term institutional ownership, we classify firms into two subgroups according to the difference in shares held by short-term (transient) and long-term (dedicated) institutional investors.¹⁸ Specifically, we construct a binary variable (*STIO indicator*) equal to

¹⁶ *PAPS* indicator takes a value of one if *PAPS* is above the top 30th percentile of the sample firms and zero if *PAPS* is below the bottom 30th percentile of the sample firms. Firms between the top 30th and the bottom 30th percentiles of the sample are dropped when we define the *PAPS* indicator.

¹⁷ The amortizable life of R&D varies across firms. For example, R&D at a pharmaceutical company should have a fairly long amortizable life because both the approval process and the patent protection granted for products that emerge from R&D are long. In contrast, R&D expenses at a software company should have a shorter amortizable life since software products emerge from research more quickly. The data on amortizable lives is downloaded from Aswath Damodaran's website (http://people.stern.nyu.edu/adamodar/New_Home_Page/spreadsh.htm).

¹⁸ Following Bushee (1998), we classify institutional investors into two groups according to their past investment behavior. Transient institutions are those that have high portfolio turnover and high diversified portfolio holdings. They tend to be short-term oriented with interest in firms' short-term trading profits. In contrast, dedicated institutions are those that have low portfolio turnovers and long-term and stable holdings, and engage less in active trading activities. We obtain the information on the types of institutions from Brian Bushee's website (<http://acct.wharton.upenn.edu/faculty/bushee/IIclass.html>).

one if in each year, a firm's short-term institutional ownership (*STIO*, the difference in ownership held by transient and dedicated institutional investors) is above the top 30th percentile of the sample and zero if it is below the bottom 30th percentile of the sample.¹⁹ We then replace two CEO age group indicators used in the above regressions with the *STIO indicator*.

Table VI Effects of Information Asymmetry, CEO Incentives, R&D Cycle, and Institutional Ownership

The results are presented in Table VI. We find that the results are generally consistent with our expectations. In Panels A and B, we find that the negative effect of *C_Score* on innovation is exacerbated when the firm is subject to greater information uncertainty and when CEO compensation is more tied to accounting performance, respectively. In Panel C, we observe that the effect is stronger when the development cycle is around 5 years and even more so when it is longer than 5 years. Finally, in Panels D and E, we find the effect is exacerbated when CEOs approach retirement (59-65 years) and when *transient* institutional ownership is more dominant, respectively. The *t*-statistics for the coefficient estimates on relevant interaction terms in the Table VI regressions range from 1.8 to 7.9. Thus, the negative effect of accounting conservatism on innovation is particularly strong when firms face high information asymmetry, when managers face high accounting performance pressure, when the product development cycle is long, or when managers' or shareholders' investment horizon is short.

Decision to Cut R&D

¹⁹ Firms between the top 30th and the bottom 30th percentiles of the sample are dropped from the regression analysis.

To further show that accounting conservatism induces managers to be short-term oriented and thus encourages them to underinvest in innovative projects, we divide our sample firms into three subgroups according to performance pressure that managers face, and examine whether our results are more pronounced when performance pressure is high. Following Bushee (1998), we define the *Decision to cut R&D* as a binary variable that takes a value of one if the change of R&D expenses per share is negative and zero otherwise. We then partition the sample into three subsamples based on the change in earnings per share: 1) the small decline subsample (SD), where earnings before R&D and taxes decline relative to the prior year, but by an amount that can be reversed by a reduction in R&D; 2) the growth subsample (IN), where firms have positive changes in pre-tax, pre-R&D earnings; these firms could maintain last year's R&D and would still have an increase in pre-tax earnings; 3) the large decline subsample (LD), where firms experience a decline in pre-tax, pre-R&D earnings greater than the amount of prior year's R&D; these firms could eliminate R&D spending and still report a decrease in pre-tax earnings. Finally, we estimate the probit regressions separately for these three subsamples in which the dependent variable is *Decision to cut R&D* and our key independent variable of interest is *C_Score*. The inclusion of other control variables follows Bushee (1998).²⁰

Table VII Effect of C_Score on Decisions to Cut R&D

Results presented in Table VII show that the effect of accounting conservatism on the decision to cut R&D is evident only for the SD subsample (column (1)) in which managers'

²⁰ Specifically, we include as controls variables institutional ownership, the change of log R&D per share in prior year, the change of log industry R&D-to-asset ratio (4-digit SIC), the change of log GDP, the change of log capital expenditure per share, the change of log sales per share, the change of log shares outstanding, leverage ratio, free cash flow over current assets, total assets, and *MB* ratio. We provide a detailed description of the construction of these variables in Appendix A.

short-term accounting performance pressure is the greatest, supporting the argument that accounting conservatism strengthens managers' incentives to meet short-term earnings goal and thus discourages them to invest in innovative projects. The negative sign of the coefficient on institutional ownership in column (1) is consistent with Bushee (1998).

Effects of C_Score on R&D Activities

Lastly, we consider the effect of accounting conservatism on R&D intensity. To this end, we regress $R\&D/Assets$ on C_Score , capital expenditures ($Capex/Assets$), and the same set of controls used in equation (1).

Table VIII Effect of C_Score on R&D Activities

Results are reported in Table VIII. In column (1), we use the full sample to estimate the regression. In column (2), we use only the subsample of firms with non-missing R&D data. We find that, in both columns, C_Score has a negative impact on a firm's R&D activities. The effect is statistically significant with t -statistics of -8.5 and -6.2, respectively. The effect is also economically significant: increasing C_Score by one standard deviation reduces R&D intensity by approximately 10%. In untabulated tests, we obtain similar results when we scale R&D expenditures by sales (the number of employees).

VI. SUMMARY AND CONCLUSION

The prior analytical literature shows that oversight system that puts too much weight on short-term incentives creates a path dependency that hinders innovation (Holmstrom (1989),

Manso (2011)). We argue that accounting conservatism plays such a role by recognizing losses early on. Although accounting conservatism mitigates the moral hazard problem by pruning projects with negative NPV, it is also more conducive to projects with limited upside potentials rather than those with large but uncertain upside potentials at a later stage. We therefore expect that firms subject to a greater degree of accounting conservatism engage less in innovative projects. In particular, we expect that this hypothesized effect is more pronounced for firms that have greater needs for innovation, firms in which managers are subject to heavier short term performance pressure, firms whose product development cycle is longer, firms in which managers and shareholders have shorter investment horizons.

Our results are consistent with these expectations. Specifically, we find that accounting conservatism is negatively associated with the number of patents and patent citations, suggesting that accounting conservatism hinders corporate innovation. Firms with a greater degree of accounting conservatism engage less in R&D effort but our results hold after controlling for this lower activity. Moreover, the cash-flows generated by innovations in firms with more conservative accounting have shorter horizons. The negative effects of accounting conservatism on innovation activities are more pronounced when firms operate in innovative industries, when the information asymmetry between managers and investors is greater, when the CEO compensation is more strongly tied to accounting performance, when the industry level R&D amortizable life is longer, when the distance to CEO retirement age is shorter, or when the pressure from short-term institutional investors is greater.

Overall, these results suggest that accounting conservatism curbs corporate innovation mainly through managerial myopia, not through firms' liquidity constraints.

Appendix A: Variable definition

Variables	Definitions
Dependent Variables	
<i>Patent (raw)</i>	Number of patents applied during the year.
<i>Citation (raw)</i>	Total number of citations summed across all patents applied by the firm during the year.
<i>Qcitation</i>	Total number of citations summed across all patents applied by the firm during the year. Each patent's number of citations is multiplied by the weighting index from Hall, Jaffe and Trajtenberg (2001, 2005).
<i>TTcitation</i>	Total number of citations summed across all patents applied by the firm during the year. Each patent's number of citations is divided by the average citation count of all patents in the same technology class and applied in the same year.
Conservatism Measures	
<i>Basu (1997) measure</i>	$X_{t-1} = \beta_1 + \beta_2 D_{t-1} + \beta_3 R_{t-1} + \beta_4 D_{t-1} R_{t-1} + \varepsilon,$ where X is earnings over the market capitalization at the prior year fiscal year end, R is return, D is a dummy variable equal to 1 when $R < 0$ and 0 otherwise. β_3 measures the incremental timeliness for bad news over good news, or conservatism. Our estimation of Basu (1997) model includes as control variables firm size, MB, leverage, an indicator for high litigation risk industries, and their interactions with D, R and $D \times R$ and is estimated as follows: $Earn_{t-1} = \alpha_0 + \alpha_1 D_{t-1} + \alpha_2 R_{t-1} + \alpha_3 D_{t-1} R_{t-1} + \alpha_4 Innovation_t + \alpha_5 Innovation_t D_{t-1} + \alpha_6 Innovation_t R_{t-1} + \alpha_7 Innovation_t D_{t-1} R_{t-1} + \alpha_8 R \& D / A_{t-1} + \alpha_9 R \& D / A_{t-1} D_{t-1} + \alpha_{10} R \& D / A_{t-1} R_{t-1} + \alpha_{11} R \& D / A_{t-1} D_{t-1} R_{t-1} + Controls_{t-1} + \varepsilon$
<i>C_Score</i>	The measure is constructed based on Basu (1997) model. Khan and Watts (2009) assume that the C_Score is a linear function of firm-specific characteristics each year: $G_Score = \beta_3 = \mu_i + \mu_2 Size_i + \mu_3 M / B_i + \mu_4 Lev_i$ $C_Score = \beta_4 = \lambda_i + \lambda_2 Size_i + \lambda_3 M / B_i + \lambda_4 Lev_i$ C_Score is the firm-year measure of conservatism, or incremental bad news timeliness. The total bad news timeliness is the sum of G_Score and C_Score. $Size$ is measured as market capitalization, M/B is the ratio of market value of equity over book value of equity, Lev is the total level of debt over market capitalization. The annual cross-sectional regression model used to estimate C_Score and G_Score is: $X_i = \beta_1 + \beta_2 D_i + R_i (\mu_i + \mu_2 Size_i + \mu_3 M / B_i + \mu_4 Lev_i) + D_i R_i (\lambda_i + \lambda_2 Size_i + \lambda_3 M / B_i + \lambda_4 Lev_i) + (\delta_1 Size_i + \delta_2 M / B_i + \delta_3 Lev_i + \delta_4 D_i Size_i + \delta_5 D_i M / B_i + \delta_6 D_i Lev_i + \varepsilon_i$
<i>C_Score (R&D adjusted)</i>	C_Score is re-estimated by adding R&D expenses back (tax-adjusted).
<i>Ball and Shivakumar (2006) measure</i>	$ACC_{t-1} = \beta_0 + \beta_1 Neg_{t-1} + \beta_2 \Delta CF_{t-1} + \beta_3 Neg_{t-1} \Delta CF_{t-1} + \varepsilon,$ where ACC is total accruals estimated as earnings before extraordinary items minus cash flows from operations scaled by total assets, ΔCF is the change in annual cash flows from operations scaled by total assets, and Neg is a dummy variable equal to one if ΔCF is negative. β_3 measures the incremental timeliness for bad news over good news, or conservatism. Our estimation of the Ball and Shivakumar (2006) model includes as control variables firm size, MB, leverage, an indicator for high litigation risk industries, and their interactions with Neg, ΔCF and $Neg \times \Delta CF$ and is estimated as follows: $ACC_{t-1} = \beta_0 + \beta_1 Neg_{t-1} + \beta_2 \Delta CF_{t-1} + \beta_3 Neg_{t-1} \Delta CF_{t-1} + \beta_4 Innovation_t + \beta_5 Innovation_t Neg_{t-1} + \beta_6 Innovation_t \Delta CF_{t-1} + \beta_7 Innovation_t Neg_{t-1} \Delta CF_{t-1} + \beta_8 R \& D / A_{t-1} + \beta_9 R \& D / A_{t-1} Neg_{t-1} + \beta_{10} R \& D / A_{t-1} \Delta CF_{t-1} + \beta_{11} R \& D / A_{t-1} Neg_{t-1} \Delta CF_{t-1} + Controls_{t-1} + \varepsilon$
<i>Negative non-operating accruals (NOA)</i>	Non-operating accruals deflated by average total assets, and averaged over a 3-year periods, multiplied by negative one. Non-operating accruals are estimated as: (Net income + Depreciation) - Operating cash flows - (Δ Accounts receivable + Δ Inventories + Δ Prepaid expenses - Δ Accounts payable - Δ Taxes payable).
Control Variables	
<i>#Employees</i>	Number of employees in thousands.
<i>Analyst coverage</i>	Median number of the 12 monthly numbers of earnings forecasts from IBES (Zero if a firm is not covered by IBES).
<i>Assets</i>	Book value of total assets.
<i>Beta</i>	CAPM beta estimated using CRSP daily stock returns each year.
<i>Board size</i>	Number of board members from RiskMetrics.
<i>Capex/Assets</i>	Capital expenditure/the beginning-of-period total assets.
<i>CEO age indicator</i>	Young or mid-age (old CEOs, CEOs older than the statutory retirement age) is a binary variable that equals one if his/her age is below or equal to 58 (between 58 and 65, older than 65) and zero otherwise.
<i>CEO delta</i>	Dollar change in CEO stock and option portfolio for 1% change in stock price, in thousands following Core and Guay (2002).
<i>CEO overconfidence indicator</i>	A binary variable equals to one for all years after the CEO holds options that are at least 67% in-the-money and zero otherwise.
<i>CEO tenure</i>	Number of year since he/she became CEO of a firm from ExecuComp.
<i>CEO vega</i>	Dollar change in CEO option holdings for a 1% change in stock return volatility, in thousands following Core and

<i>Change in Capex</i>	Guay (2002).
<i>Change in GDP</i>	$\Delta \text{Ln}(\text{Capex per share})_t$
<i>Change in industry R&D-to-assets ratio</i>	$\Delta \text{Ln}(\text{GDP})_t$
<i>Change in no. of shares outstanding</i>	$\Delta \text{Ln}(\text{Total R\&D expenditures of other firms in the same 4-digit SIC code industry scaled by total sales of other firms in the same 4-digit SIC industry})_t$
<i>Change in sales</i>	$\Delta \text{Ln}(\text{Total shares outstanding})_t$
<i>Cut in R&D</i>	$\Delta \text{Ln}(\text{Sales per share})_t$
<i>Firm age</i>	A binary variable that equals one if the R&D per share is reduced relative to the prior year and zero otherwise.
<i>Free cash flow/Current assets</i>	Number of years since the firm entered CRSP.
<i>G-index</i>	$(\text{Operating cash flows}_t - \text{Average Capex}_{t-1 \text{ to } t-3}) / \text{Current assets}_{t-1}$
<i>Hadlock and Pierce (2010) index</i>	Gompers, Ishii, and Metrick (2003) governance index from Risk Metrics
<i>Herfindahl</i>	$-0.737 * \text{Size} + 0.043 * \text{Size}^2 + 0.04 * \text{Firm age}$.
<i>Independent directors (%)</i>	Industry Herfindahl index based on all Compustat firms, where industries are defined by 3-digit SIC.
<i>Information asymmetry (IA) indicator</i>	Number of independent directors / Board size from RiskMetrics.
<i>Innovative industry indicator</i>	A binary variable that equals one if the standard deviation of long-term growth analyst forecast scaled by the mean forecast is above the top 30th percentile of the sample each year and zero if it is below the bottom 30th percentile of the sample each year.
<i>Institutional ownership</i>	An industry is innovative if the industry level (2-digit SIC) <i>Qcitation</i> is above the sample median each year.
<i>Kaplan and Zingales (1997) index</i>	Shares owned by institutional investors/total shares outstanding from CDA/Spectrum Institutional (13f) Holdings.
<i>Leverage</i>	$-1.002 * \text{Cash flow}/\text{Assets} - 39.368 * \text{Dividend}/\text{Assets} - 1.315 * \text{Cash}/\text{Assets} + 3.139 * \text{Total debt}/\text{Assets} + 0.283 * \text{Tobin's } q$
<i>Liquidity</i>	$(\text{Short-term debt} + \text{Long-term debt}) / \text{Assets}$.
<i>Litigation</i>	Cash scaled by total assets.
<i>Lottery</i>	A binary variable that equals one if a firm falls in high litigation risk industry as identified by SIC codes: 2833-2836, 3570-3577, 3600-3674, 5200-5961, and 7370-7379.
<i>MB</i>	A binary variable that equals one if a stock has both above-median idiosyncratic volatilities and above-median idiosyncratic skewness and zero otherwise (Kumar (2009)).
<i>OCF_{t+n}</i>	Market value of equity/Book value of equity.
<i>PAPS indicator</i>	Operating cash flows _{t+n} /Assets _{t-1}
<i>PPE/#Employees</i>	A binary variable that equals one if the sensitivity of CEO pay to accounting performance (PAPS) in a firm is above the top 30th percentile and zero if it is below the bottom 30th percentile of the sample. PAPS (β_1) is estimated during 1992-1997 by conducting the time-series regression for each firm following Leone, Wu, and Zimmerman (2006):
<i>Prior change in R&D</i>	$\text{Ln}(\text{Total compensation}) = \beta_0 + \beta_1 \text{ROA} + \beta_1 \text{Stock return} + \beta_2 \text{Ln}(\text{Sales}) + \beta_3 \text{Ln}(\text{Sales})^2 + \varepsilon$
<i>ROA</i>	Net property, plant, and equipment per employee in thousands.
<i>R&D cycle indicator</i>	$\Delta \text{Ln}(\text{R\&D per share})_{t-1}$
<i>R&D/Assets</i>	Operating income before depreciation and amortization (EBITDA)/Assets.
<i>SAB 101 indicator</i>	Short (mid, long) R&D cycle is a binary variable that equals one if amortizable lives are shorter than 5 years (5 years, longer than 5 years) and zero otherwise.
<i>Sales</i>	R&D expenses/Assets. Missing R&D expenses are treated as zero.
<i>Sales growth</i>	A binary variable to denote the enactment of the SEC's Staff Accounting Bulletin No. 101 in 1999.
<i>Size</i>	Book value of total sales.
<i>STIO indicator</i>	Change in net sales scaled by the lagged net sales.
<i>Stock return</i>	$\text{Ln}(\text{Assets})$.
<i>Stock volatility</i>	A binary variable that equals one if the difference in a firm's ownership held by transient institutional investors and dedicated institutional investors is above the top 30th percentile of the sample each year, and zero if it is below the bottom 30th percentile of the sample each year.
<i>Total compensation</i>	Compounded monthly stock returns over the fiscal year.
<i>Union</i>	Annualized standard deviation of monthly stock return over the past 12-months.
<i>Whited and Wu (2006) index</i>	Salary + Bonus + Restricted stocks + Stock options + Long-term incentive awards from ExecuComp
	Percentage of workforce in an industry employed by unions. The data is downloaded from the website maintained by Barry Hirsch and David Macpherson (www.unionstats.com).
	$-0.091 * \text{Cash flow}/\text{Assets} - 0.062 * \text{Dividend pay-out indicator} + 0.021 * \text{Long-term debt}/\text{Assets} - 0.044 * \text{Size} + 0.102 * \text{Industry sales growth} - 0.035 * \text{Sales growth}$

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Table I
Summary statistics

The sample consists of 70,871 firm-years covered by both Compustat and the NBER Patent and Citation Database between 1976 and 2003. *Qcitation* and *TTcitation* are adjusted using the weighting index of Hall, Jaffe, and Trajtenberg (2001) and the method of time-technology class fixed effect, respectively. The detailed definitions of variables are described in Appendix A. 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.

Variables	Mean	Standard Deviation	Q1	Median	Q3
	(1)	(2)	(3)	(4)	(5)
<i>Panel A: Innovation measures</i>					
<i>Patent (raw)</i>	5.71	18.13	0.00	0.00	1.00
<i>Citation (raw)</i>	107.50	810.56	0.00	0.00	7.00
<i>Qcitation</i>	180.76	1495.95	0.00	0.00	13.17
<i>TTcitation</i>	14.00	99.36	0.00	0.00	1.19
<i>Panel B: Mean patent and citation counts by firms' accounting conservatism</i>					
<i>C_Score ranking</i>	<i>N</i>	<i>Patent (raw)</i>	<i>Citation (raw)</i>	<i>Qcitation</i>	<i>TTcitation</i>
Lowest	14,184	18.89	419.58	735.37	55.64
2	14,171	5.17	64.32	94.14	7.88
3	14,166	2.37	27.18	39.79	3.35
4	14,171	1.42	18.31	24.12	2.14
Highest	14,179	0.70	7.84	9.94	0.96
Lowest - Highest	-	18.20	411.73	725.43	54.68
(<i>p</i> -value)	-	(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)
<i>Panel C: Firm characteristics</i>					
<i>Assets (\$millions)</i>	1,965.78	6,456.80	60.27	213.12	916.16
<i>MB</i>	2.86	4.00	1.04	1.73	3.02
<i>Sales growth</i>	0.14	0.34	0.00	0.11	0.23
<i>PPE/#Employees (\$thousands)</i>	112.27	319.40	18.01	32.54	69.05
<i>Leverage</i>	0.22	0.18	0.06	0.20	0.34
<i>Liquidity</i>	0.15	0.18	0.02	0.07	0.20
<i>Stock volatility</i>	0.03	0.02	0.02	0.03	0.04
<i>Stock return</i>	0.16	0.62	-0.22	0.07	0.39
<i>ROA</i>	0.06	0.18	0.03	0.09	0.14
<i>R&D/Assets</i>	0.04	0.08	0.00	0.00	0.05
<i>Analyst coverage (Number of Analysts)</i>	4.86	6.75	0.00	2.00	7.00
<i>Firm age (Years)</i>	15.69	14.71	5.00	11.00	20.00
<i>Herfindahl</i>	0.20	0.17	0.09	0.14	0.24
<i>C_Score</i>	0.10	0.12	0.04	0.10	0.17

Table II
Pearson correlation matrix

The sample consists of 70,871 firm-years covered by both Compustat and the NBER Patent and Citation Database between 1976 and 2003. *Qcitation* and *TTcitation* are adjusted using the weighting index of Hall, Jaffe, and Trajtenberg (2001) and the method of time-technology class fixed effect, respectively. The detailed definitions of variables are described in Appendix A. 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. Correlations significant at the 5% level are in bold.

Variable	Ln(Patent)	Ln(Q citation)	Ln(TT citation)	C_Score	R&D/ Assets	Ln(PPE/ #Employees)	Leverage	Liquidity	Size	MB	Sales growth	Stock volatility	Stock return	ROA	Ln(Analyst coverage)	Ln(Firm age)
Ln(Qcitation)	0.940															
Ln(TTcitation)	0.964	0.966														
C_Score	-0.315	-0.308	-0.313													
R&D/Assets	0.151	0.165	0.140	0.044												
Ln(PPE/#Employees)	0.103	0.072	0.091	-0.172	-0.096											
Leverage	-0.064	-0.081	-0.063	0.103	-0.265	0.247										
Liquidity	0.012	0.024	0.008	0.040	0.472	-0.122	-0.442									
Size	0.445	0.376	0.419	-0.493	-0.254	0.364	0.212	-0.269								
MB	0.032	0.034	0.031	-0.141	0.298	-0.006	0.011	0.212	-0.140							
Sales growth	-0.035	-0.020	-0.026	-0.051	0.037	-0.010	-0.003	0.073	-0.061	0.154						
Stock volatility	-0.182	-0.175	-0.177	0.396	0.319	-0.120	-0.022	0.246	-0.467	0.183	0.053					
Stock return	0.025	0.029	0.026	0.009	0.015	-0.023	-0.028	0.001	0.007	-0.095	-0.040	-0.136				
ROA	0.068	0.070	0.074	-0.208	-0.547	-0.011	0.007	-0.306	0.290	-0.261	0.066	-0.458	0.071			
Ln(Analyst coverage)	0.375	0.349	0.366	-0.407	-0.002	0.209	-0.026	-0.040	0.652	0.038	0.007	-0.250	-0.021	0.176		
Ln(Firm age)	0.294	0.257	0.275	-0.197	-0.187	0.074	0.056	-0.261	0.441	-0.163	-0.222	-0.365	0.027	0.187	0.246	
Herfindahl index	-0.005	0.004	-0.002	-0.018	-0.152	-0.008	0.043	-0.121	0.021	-0.057	-0.038	-0.104	-0.004	0.078	-0.046	0.087

Table III
Effect of *C_Score* on innovation outputs

The sample consists of firms covered by both Compustat and the NBER Patent and Citation Database between 1976 and 2003. *Qcitation* and *TTcitation* are adjusted using the weighting index of Hall, Jaffe, and Trajtenberg (2001) and the method of time-technology class fixed effect, respectively. The detailed definitions of variables are described in Appendix A. 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. 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>Predicted sign</i>	<i>Ln(1+Patent)</i>	<i>Ln(1+Qcitation)</i>	<i>Ln(1+TTcitation)</i>
		OLS	OLS	OLS
		(1)	(2)	(3)
<i>C_Score</i>	+	-0.318*** (-5.6)	-0.666*** (-6.6)	-0.407*** (-6.9)
R&D/Assets	+	2.068*** (15.1)	4.006*** (15.5)	1.978*** (13.3)
Ln(PPE/#Employees)	+	0.006 (0.5)	0.014 (0.7)	0.006 (0.5)
Leverage	-	-0.397*** (-7.5)	-0.676*** (-7.4)	-0.397*** (-7.2)
Liquidity	+	0.168*** (3.3)	0.359*** (3.9)	0.166*** (3.0)
Size	+	0.293*** (21.3)	0.438*** (21.0)	0.281*** (19.7)
MB	+	0.018*** (10.4)	0.027*** (8.9)	0.018*** (9.7)
Sales growth	+	0.007 (0.7)	0.041* (1.9)	0.019 (1.6)
Stock volatility	+	3.496*** (9.0)	4.450*** (6.5)	3.780*** (9.2)
Stock return	+	0.051*** (9.6)	0.113*** (10.8)	0.061*** (10.4)
ROA	+	0.168*** (3.5)	0.405*** (4.5)	0.181*** (3.5)
Ln(Analyst coverage)	-	0.071*** (3.8)	0.191*** (6.3)	0.096*** (4.9)
Ln(Firm age)	+	0.139*** (10.2)	0.215*** (9.6)	0.133*** (9.6)
Herfindahl	+	0.134 (0.7)	0.400 (1.3)	0.159 (0.8)
Herfindahl ²	-	-0.011 (-0.1)	-0.178 (-0.5)	-0.036 (-0.2)
Constant		-1.426*** (-12.4)	-1.906*** (-10.1)	-1.358*** (-11.3)
Industry fixed effects		Yes	Yes	Yes
Year fixed effects		Yes	Yes	Yes
Sample size		70,871	70,871	70,871
Adjusted R-squared		0.43	0.40	0.40

Table IV
Effect of C_Score on innovation horizon

The sample consists of firms covered by both Compustat and the NBER Patent and Citation Database between 1976 and 2003. $Qcitation$ and $TTcitation$ are adjusted using the weighting index of Hall, Jaffe, and Trajtenberg (2001) and the method of time-technology class fixed effect, respectively. A high (low) C_Score firm is the one whose C_Score is above (below) the sample median of C_Score in a certain year. Each subsample consists of 13,689 observations. Operating cash flows in year $t+1$, $t+3$, and $t+5$ are regressed against innovation measures and control variables (R&D expenditure over assets, firm size, market-to-book ratio, leverage, beta, and industry indicators), but for the sake of brevity, the regression estimates for control variables are not reported. The detailed definitions of variables are described in Appendix A. 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. 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.

	OCF_{t+1}	OCF_{t+3}	OCF_{t+5}	Test of equal coefficients between year $t+5$ and $t+1$
	OLS	OLS	OLS	
	(1)	(2)	(3)	(4)
<i>Panel A: Effect of Patent on future operating cash flows</i>				
<i>A1: Low C_Score subsample</i>				
$\ln(1+Patent)_t$	0.009*** (5.6)	0.012*** (4.8)	0.014*** (3.8)	$\chi^2 = 2.80$ $p\text{-value} = 0.09$
<i>A2: High C_Score subsample</i>				
$\ln(1+Patent)_t$	0.007** (2.0)	0.004 (0.8)	0.001 (0.1)	$\chi^2 = 0.79$ $p\text{-value} = 0.37$
<i>Panel B: Effect of $Qcitation$ on future operating cash flows</i>				
<i>B1: Low C_Score subsample</i>				
$\ln(1+Qcitation)_t$	0.006*** (6.3)	0.008*** (5.6)	0.010*** (4.2)	$\chi^2 = 3.86$ $p\text{-value} = 0.05$
<i>B2: High C_Score subsample</i>				
$\ln(1+Qcitation)_t$	0.003* (1.9)	0.002 (0.7)	0.001 (0.4)	$\chi^2 = 0.21$ $p\text{-value} = 0.65$
<i>Panel C: Effect of $TTcitation$ on future operating cash flows</i>				
<i>C1: Low C_Score subsample</i>				
$\ln(1+TTcitation)_t$	0.009*** (5.9)	0.013*** (5.5)	0.015*** (4.3)	$\chi^2 = 4.78$ $p\text{-value} = 0.03$
<i>C2: High C_Score subsample</i>				
$\ln(1+TTcitation)_t$	0.005* (1.8)	0.005 (1.1)	0.007 (0.9)	$\chi^2 = 0.09$ $p\text{-value} = 0.77$

Table V

Effect of *C_Score* on lottery-like feature of innovation

The sample consists of firms covered by both Compustat and the NBER Patent and Citation Database between 1976 and 2003. *Qcitation* and *TTcitation* are adjusted using the weighting index of Hall, Jaffe, and Trajtenberg (2001) and the method of time-technology class fixed effect, respectively. Following Kumar (2009), *Lottery* is a binary variable that equals one if a stock has both above-median idiosyncratic volatilities and above-median idiosyncratic skewness and zero otherwise. Coefficient estimates reported are the marginal effects that measure the effect of a one unit change in continuous explanatory variables (moving from 0 to 1 for dummy variables) on the dependent variable. The detailed definitions of variables are described in Appendix A. 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. The *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.

	Lottery		Lottery		Lottery	
	C_Score <= median	C_Score >= median	C_Score <= median	C_Score >= median	C_Score <= median	C_Score >= median
	Probit (1)	Probit (2)	Probit (3)	Probit (4)	Probit (5)	Probit (6)
Ln(1+Patent)	0.002 (1.2)	-0.020*** (-3.3)				
Ln(1+Qcitation)			0.002 (1.6)	-0.005** (-2.2)		
Ln(1+TTcitation)					0.003 (1.5)	-0.011** (-2.1)
R&D/Assets	0.046 (1.2)	0.144** (2.4)	0.043 (1.2)	0.132** (2.2)	0.045 (1.2)	0.130** (2.2)
Ln(PPE/#Employees)	0.003 (1.4)	-0.015*** (-3.8)	0.003 (1.3)	-0.015*** (-3.9)	0.003 (1.3)	-0.015*** (-3.9)
Leverage	0.156*** (11.3)	0.379*** (16.2)	0.156*** (11.3)	0.381*** (16.3)	0.156*** (11.3)	0.381*** (16.3)
Liquidity	0.043*** (3.4)	0.024 (1.1)	0.043*** (3.4)	0.023 (1.0)	0.043*** (3.4)	0.023 (1.0)
Size	-0.048*** (-24.7)	-0.078*** (-18.9)	-0.048*** (-25.4)	-0.079*** (-19.4)	-0.048*** (-25.1)	-0.079*** (-19.3)
MB	-0.003*** (-5.6)	-0.011*** (-8.3)	-0.003*** (-5.6)	-0.011*** (-8.3)	-0.003*** (-5.6)	-0.011*** (-8.3)
Sales growth	0.016*** (2.8)	-0.017* (-1.8)	0.016*** (2.8)	-0.017* (-1.8)	0.016*** (2.8)	-0.017* (-1.8)
Stock return	0.046*** (15.8)	0.138*** (29.6)	0.046*** (15.8)	0.138*** (29.6)	0.046*** (15.8)	0.138*** (29.6)
ROA	-0.310*** (-19.3)	-0.667*** (-24.8)	-0.311*** (-19.4)	-0.667*** (-24.8)	-0.311*** (-19.4)	-0.667*** (-24.8)
Ln(Analyst coverage)	-0.008*** (-2.9)	-0.013** (-2.1)	-0.008*** (-3.0)	-0.013** (-2.1)	-0.008*** (-3.0)	-0.013** (-2.1)
Ln(Firm age)	-0.022*** (-8.9)	-0.049*** (-9.9)	-0.022*** (-8.9)	-0.049*** (-9.9)	-0.022*** (-8.9)	-0.049*** (-10.0)
Herfindahl index	-0.117*** (-3.3)	-0.223*** (-3.7)	-0.117*** (-3.3)	-0.223*** (-3.7)	-0.117*** (-3.3)	-0.223*** (-3.7)
Herfindahl index ²	0.107** (2.4)	0.210*** (2.8)	0.106** (2.4)	0.209*** (2.8)	0.106** (2.4)	0.209*** (2.8)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	35,359	35,373	35,359	35,373	35,359	35,373
Pseudo R-squared	0.25	0.17	0.25	0.17	0.25	0.17
Test of equal coefficients for innovation measures between high and low C_Score groups	$\chi^2 = 12.75$ $p\text{-value} = 0.00$		$\chi^2 = 7.82$ $p\text{-value} = 0.01$		$\chi^2 = 7.43$ $p\text{-value} = 0.01$	

Table VI

Effects of information asymmetry, CEO incentives, R&D cycle, and institutional ownership

The sample consists of firms covered by both Compustat and the NBER Patent and Citation Database between 1976 and 2003. *Qcitation* and *TTcitation* are adjusted using the weighting index of Hall, Jaffe, and Trajtenberg (2001) and the method of time-technology class fixed effect, respectively. All regressions include the same control variables as those used in the Table III regressions except for Panel C where *Ln(CEO tenure)* is included as an additional control variable. For the sake of brevity, the regression estimates for control variables are not reported. In Panel A, a firm is classified as a low (high) information asymmetry firm if the standard deviation of long-term growth analyst forecast scaled by the mean forecast is below the bottom (above the top) 30th percentile of the sample each year. *IA* indicator equals one for high information asymmetry firms and zero for low information asymmetry firms. In Panel B, a firm is classified as a high (low) CEO pay-accounting-performance sensitivity (*PAPS*) firm if the *PAPS* is above the top (below the bottom) 30th percentile of the sample. *PAPS* indicator equals one for high *PAPS* firms and zero for low *PAPS* firms. In Panel C, an industry is classified as a mid (long) R&D cycle industry if its amortizable life is 5 years (longer than 5 years). In Panel D, a CEO is classified as a young or mid (old) age CEO if her age is below or equal to 58 (between 58 and 65). In Panel E, a firm is classified as a low (high) short-term institutional ownership firm if the difference in a firm's ownership held by transient and dedicated institutional investors is below the bottom (above the top) 30th percentile of the sample each year. *STIO* indicator equals one for high short-term institutional ownership firms, and zero for low short-term institutional ownership firms. The detailed definitions of variables are described in Appendix A. 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. 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.

Dependent variables	<i>Ln(1+Patent)</i>	<i>Ln(1+Qcitation)</i>	<i>Ln(1+TTcitation)</i>
	OLS (1)	OLS (2)	OLS (3)
<i>Panel A: Effect of information asymmetry</i>			
C_Score	0.197 (0.8)	0.019 (0.0)	0.117 (0.5)
C_Score × IA indicator	-0.748** (-2.5)	-0.900* (-1.8)	-0.739** (-2.3)
IA indicator	0.089** (2.1)	0.107 (1.5)	0.078* (1.7)
Sample size	17,561	17,561	17,561
<i>Panel B: Effect of sensitivity of CEO pay to accounting performance</i>			
C_Score	0.067 (0.1)	-0.203 (-0.2)	-0.064 (-0.1)
C_Score × PAPS indicator	-1.503** (-2.2)	-2.939*** (-2.8)	-1.979*** (-2.8)
PAPS indicator	0.115 (1.0)	0.265 (1.5)	0.183 (1.6)
Sample size	3,246	3,246	3,246
<i>Panel C: Effect of R&D cycle</i>			
C_Score	1.194*** (9.9)	1.727*** (8.4)	1.172*** (9.3)
C_Score × mid R& D cycle indicator	-1.458*** (-7.7)	-2.352*** (-7.5)	-1.532*** (-7.7)
C_Score × long R&D cycle indicator	-3.062*** (-14.9)	-4.777*** (-14.5)	-3.178*** (-14.7)
Mid R& D cycle indicator	0.125 (0.8)	0.251 (1.0)	0.164 (1.0)
Long R&D cycle indicator	0.226 (1.4)	0.261 (1.1)	0.186 (1.1)
Sample size	70,039	70,039	70,039
<i>Panel D: Effect of distance to CEO retirement age</i>			
C_Score	0.001 (0.0)	-0.100 (-0.1)	-0.060 (-0.1)
C_Score × Young or mid age CEO indicator	-0.816 (-1.3)	-1.559 (-1.5)	-0.968 (-1.5)
C_Score × Old CEO indicator	-1.656*** (-2.6)	-2.580** (-2.4)	-1.641** (-2.4)
Young or mid age CEO indicator	0.126 (1.4)	0.219 (1.4)	0.135 (1.4)
Old CEO indicator	0.260*** (2.9)	0.429*** (2.8)	0.244** (2.6)
Sample size	11,258	11,258	11,258
<i>Panel E: Effect of short-term institutional ownership</i>			
C_Score	-0.139 (-1.0)	-0.381 (-1.6)	-0.185 (-1.3)
C_Score × STIO indicator	-0.508*** (-2.7)	-0.929*** (-3.0)	-0.676*** (-3.4)
STIO indicator	-0.037 (-1.1)	0.033 (0.6)	-0.000 (-0.0)
Sample size	37,215	37,215	37,215

Table VII
Effect of *C_Score* on decision to cut R&D

The sample consists of firms covered by both Compustat and the NBER Patent and Citation Database between 1976 and 2003. Following Bushee (1998), the sample is partitioned into three subsamples based on the change in earnings per share: 1) the small decline subsample (SD), where earnings before R&D and taxes decline relative to the prior year, but by an amount that can be reversed by a reduction in R&D; 2) the growth subsample (IN), where firms have positive changes in pre-tax, pre-R&D earnings; 3) the large decline subsample (LD), where firms experience a decline in pre-tax, pre-R&D earnings greater than the amount of prior year's R&D. *Qcitation* and *TTcitation* are adjusted using the weighting index of Hall, Jaffe, and Trajtenberg (2001) and the method of time-technology class fixed effect, respectively. *Cut in R&D* is a binary variable that equals one if R&D per share is cut relative to the prior year and zero otherwise. Coefficient estimates reported are the marginal effects that measure the effect of a one unit change in continuous explanatory variables (moving from 0 to 1 for dummy variables) on the dependent variable. The detailed definitions of variables are described in Appendix A. 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. The *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>Dependent variable = Cut in R&D</i>		
	SD sample	IN sample	LD sample
	Probit (1)	Probit (2)	Probit (3)
<i>C_Score</i>	0.274** (2.5)	-0.016 (-0.4)	-0.038 (-0.9)
Institutional ownership	-0.090** (-2.6)	-0.023 (-1.5)	0.002 (0.1)
Prior Δ R&D	0.013 (0.3)	-0.021 (-1.0)	0.085*** (2.7)
Δ Industry R&D-to-assets ratio	-0.967* (-1.9)	-0.342 (-1.5)	0.349 (1.1)
Δ GDP	1.063 (1.2)	0.158 (0.5)	-0.001 (-0.0)
Δ Capex	-0.143*** (-6.5)	-0.070*** (-11.5)	-0.015** (-2.4)
Δ Sales	-0.227*** (-8.1)	-0.162*** (-15.7)	-0.240*** (-18.3)
Δ No. of shares outstanding	0.860*** (16.7)	0.176*** (10.2)	0.068*** (4.4)
Leverage	0.135** (2.6)	-0.220*** (-10.5)	-0.186*** (-7.7)
Free cash flow/Current assets	-0.069*** (-3.0)	-0.048*** (-6.2)	0.027*** (3.2)
Size	0.007 (1.3)	-0.011*** (-4.0)	0.009*** (2.8)
MB	-0.004 (-1.6)	0.005*** (6.1)	0.006*** (4.7)
Industry fixed effects	No	No	No
Year fixed effects	Yes	Yes	Yes
Sample size	6,050	30,060	22,110
Pseudo R-squared	0.11	0.06	0.08

Table VIII
Effect of C_Score on R&D activities

The sample consists of firms covered by both Compustat and the NBER Patent and Citation Database between 1976 and 2003. In column (1), the full sample is used to estimate the regression and in column (2), only the subsample of firms with non-missing R&D is used to estimate the regression. The detailed definitions of variables are described in Appendix A. 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. 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&D/Assets (full sample)</i>	<i>R&D/Assets (subsample of firms with non-missing R&D)</i>
	OLS (1)	OLS (2)
C_Score	-0.030*** (-8.5)	-0.033*** (-6.2)
Capex/Assets	-0.003 (-0.8)	0.007 (1.0)
Ln(PPE/#Employees)	0.001*** (2.7)	-0.001 (-1.4)
Leverage	-0.035*** (-12.7)	-0.049*** (-11.8)
Liquidity	0.111*** (25.3)	0.108*** (20.5)
Size	-0.004*** (-9.0)	-0.005*** (-8.6)
MB	0.001*** (5.8)	0.001*** (3.8)
Sales growth	0.005*** (3.2)	0.003 (1.4)
Stock volatility	0.282*** (9.1)	0.493*** (10.9)
Stock return	-0.001* (-1.9)	-0.004*** (-6.0)
ROA	-0.169*** (-33.3)	-0.176*** (-31.4)
Ln(Analyst coverage)	0.010*** (17.2)	0.012*** (13.3)
Ln(Firm age)	-0.001** (-2.5)	-0.002* (-1.9)
Herfindahl	-0.092*** (-12.6)	-0.097*** (-8.8)
Herfindahl ²	0.083*** (10.1)	0.087*** (6.8)
Constant	0.048*** (13.8)	0.074*** (14.3)
Industry fixed effects	Y	Y
Year fixed effects	Y	Y
Sample size	69,988	42,272
Adjusted R-squared	0.49	0.51

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