Does Accounting Conservatism Impede Corporate Innovation?*

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ABSTRACT

We examine the impact of accounting conservatism on corporate innovation. We find that firms that exhibit a higher degree of accounting conservatism generate fewer patents. Their patents also generate fewer citations and lower economic benefits. These effects of accounting conservatism on innovation are more pronounced when firms' need for innovation is higher, when the product development cycle is longer, when managers have higher pay sensitivity to accounting performance, or when managers are more myopic. Overall, our findings suggest that accounting conservatism curbs corporate innovation by exacerbating the effects of managerial myopia.

I. INTRODUCTION

Corporate innovation has become an increasingly important element of corporate strategy that drives firms' long-term growth and competitiveness but this topic has received relatively little attention in the accounting literature. Whether accounting affects corporate innovation remains largely unanswered. We investigate this question by examining the role of conditional accounting conservatism in corporate innovation.[1] The principle of conditional 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. Watts (2003) and Francis and Martin (2010), for example, show that accounting conservatism can act as an important governance mechanism that deters managers from undertaking negative net present value (NPV) projects by accelerating future investment losses into current earnings.

However, we argue that accounting conservatism can curb corporate innovation by exacerbating the effects of managerial myopia. Prior research shows that managers are under pressure to meet certain short-term accounting objectives (e.g., positive or increasing income or a certain level of earnings per share) and cut their R&D effort if R&D spending jeopardizes their ability to reach these goals.[2] Accounting conservatism exacerbates the effects of this managerial myopia because the asymmetric treatment of good and bad news increases the likelihood of missing these targets and thus raises the propensity to reduce R&D effort. In the absence of accounting conservatism, managers who are under pressure to achieve short-term accounting-

[1] Innovation can come from various different sources and does not necessarily involve a structured R&D process. Strictly speaking, our study focuses more on "invention" rather than on "innovation" (Schumpeter, 1947). However, to be consistent with the recent literature (e.g., Acharya and Subramanian, 2009; Atanassov, 2012), we maintain this terminology.
[2] See among others, Baber, Fairfield, and Haggard (1991), Bushee (1998), Bens et al. (2003), and Garcia Osma and Young (2009). We review this literature in greater detail in Section II.

based objectives may delay the recognition of bad news, and thus be able to avoid cutting investment in R&D for accounting reasons. Realizing the possibility that they may have to interrupt their effort (*ex post*), managers of firms with conservative accounting may decide (*ex ante*) to avoid multi-stage long-term innovative research projects with potentially large pay-offs if there is a risk that these projects will be affected by an economic shock (unrelated to the R&D). [3] This reasoning also suggests that the effect of conservatism on innovation is exacerbated in firms where managers or shareholders are more myopic, such as those where managers' pay is more sensitive to accounting performance or where pressure from short-term institutional investors is greater.

Consistent with our predictions, we find that accounting conservatism is negatively associated with the quantity and quality of innovation as measured by the number of patents and patent citations, respectively. Firms with a greater degree of accounting conservatism also engage less in R&D activities but our main results hold after controlling for the level of R&D activities. These results are both economically and statistically significant, and robust to a variety of model specifications. We also perform a battery of tests to mitigate potential endogeneity concerns about the relation between conservatism and innovation, and find that our conclusion remains unaffected.

Further supporting our argument, we find that the negative effects of accounting conservatism on innovation are more pronounced when: 1) the product development cycle is longer (and thus more likely to be interrupted by a negative shock), 2) managers are subject to higher accounting performance pressure (i.e., CEO compensation is strongly linked to accounting performance), 3) managers or shareholders have shorter investment horizons (i.e., the

[3] Our results reported in Section V indicate that volatility in the R&D effort reduces its productivity, making delays in its exertion economically costly.

distance to CEO retirement is shorter or short-term institutional ownership is larger), 4) managers have a higher degree of myopia, 5) it is more difficult for firms to manipulate their accruals, or 6) firms' need for innovation is higher (i.e., firms operating in innovative industries).

Finally, we find that inventions made by conservative firms are of lower quality than those made by "liberal" firms. Aside from generating fewer citations, we find that patents of firms with conservative accounting generate lower and more short-term cash-flows, trigger less positive stock market reaction to the news that they have been granted, and are less likely to be "blockbusters".

Our study contributes to the literature by considering how accounting properties 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 high-quality reporting improves the investment process. We extend this research by showing that a reporting property that is often desirable can also have a negative effect on the innovative nature of investment by setting a perverse incentive for managers, particularly at firms subject to high short-term performance pressure and those that rely heavily on innovation.[4] Thus, our study is related to Roychowdhury (2010) who raises the issue regarding whether accounting conservatism leads managers to underinvest in risky projects.

More specifically, we take both *ex ante* and *ex post* views. Previous research on real earnings management shows that managers behave opportunistically by cutting their expenditure on R&D to avoid missing certain accounting benchmarks. We extend this research by showing that opportunistic managerial behavior is exacerbated when the level of accounting conservatism is high. In particular, we find that firms are more likely to cut R&D to reverse an earnings

[4] Given that prior literature has already documented many positive attributes associated with conservatism, our study does not conclude that conservatism is on balance a negative attribute.

decline when their accounting is more conservative. More importantly, we find that this *ex post* behavior has consequences on the amount and the type of innovation projects that the firm elects to invest in *ex ante*, suggesting that conservative accounting leads to conservative innovation and exacerbates the effects of managerial myopia.

The remainder of the paper proceeds as follows. We develop our main hypothesis in Section II. In Section III, we present our sample, summary statistics, and the construction of key variables. We discuss our main empirical results in Section IV and conduct further analyses in Section V. Section VI summarizes our findings and draws conclusions.

II. HYPOTHESIS DEVELOPMENT

Watts (2003) defines accounting conservatism as the differential verifiability required for recognition of losses versus profits. He also reasons that firms practice conservative accounting in response to economic demand for verifiable and timely information that mitigates agency problems in contracting, and in response to changes in the regulatory and litigation environments. Watts (2003) and Francis and Martin (2010) further show that accounting conservatism serves as an important governance mechanism in deterring managers from undertaking negative NPV projects.

We depart from this line of literature by considering whether accounting conservatism has a dysfunctional effect on managers engaged in R&D projects and whether it curbs innovation. It is important to note that the mechanism whereby accounting conservatism affects corporate innovation is not an asymmetric accounting treatment of R&D spending, but a combination of asymmetric accounting treatment of non-R&D activities and managerial myopia. Under the US

Generally Accepted Accounting Principles (GAAP), R&D costs are typically expensed,[5] hence it is unlikely that conservatism affects firms' accounting treatment of R&D costs asymmetrically.

We start with the premise that any substantial innovative project will take years of effort before delivering positive results (e.g., Holmstrom, 1989). A sufficiently patient or well-informed principal may wait for these benefits to materialize. Knowing this, a manager who is properly compensated for taking risk may decide to invest in projects with a large, albeit uncertain, pay-off. To the extent that equity can be viewed as a call option on the firm's assets, investing in such projects may be valuable for shareholders. However, if the firm's reporting system and incentive policy put pressure on managers to deliver minimum profitability in the short run, managers facing bad news that is unrelated to innovation activities may be tempted to cut investment in innovation when earnings would otherwise fall short of this minimum requirement.

In our setting, such managerial myopia does not arise from a cognitive bias; rather, the manager who tries to maximize the long-term value of the firm is subject to constraints that lead her "to focus more heavily on short-term profits rather than on long-term objectives" (Stein, 1988). The existing analytical literature proposes several models built on this intuition and shows that myopia can be consistent with optimal contracting (e.g., Narayanan, 1987; Stein, 1988; Fudenberg and Tirole, 1995; von Thadden, 1995; Bolton, Scheinkman, and Xiong, 2006). This literature suggests the risk of losing employment (Fudenberg and Tirole, 1995), managerial compensation (Narayanan, 1985; Noe and Rebello, 1997), stock price pressure (Stein, 1988), and the need to cater to the short-term demands of transient investors (Bolton, Scheinkman, and Xiong, 2006) as the major sources of myopia. Although the origin of constraints that lead to

[5] SFAS 2 prohibits the capitalization of R&D costs for fiscal years beginning on or after January 1, 1975. However, there are some exceptions to this general rule such as purchased R&D or certain software development costs. We address these possibilities in our robustness checks described in Section IV.

managerial myopia is largely outside the scope of our study, we examine several settings in which it is more likely to be present in Section V.B.

Consistent with the presence of this myopic behavior affecting innovation, Baber, Fairfield, and Haggard (1991) find that R&D spending is significantly lower when it jeopardizes the ability to report positive or increasing income in the current period. Dechow and Sloan (1991) show that CEOs spend relatively less on R&D in their final years in office. Bens et al. (2003) show that managers cut R&D when earnings per share is diluted by managers' stock option exercises. Graham, Harvey, and Rajgopal (2005) who survey a large number of CFOs in the US find that a majority of CFOs are willing to sacrifice long-term firm value to meet the desired short-term earnings targets. In particular, 80% of survey participants report that they would cut R&D as well as other discretionary expenditure to meet earnings targets. Garcia Osma and Young (2009) find that the pressure to report positive levels and changes of earnings in a large sample of R&D-active UK firms leads to contemporaneous cuts in R&D expenditure. Cutting R&D is different from cutting capital expenditures as reducing R&D increases pre-tax earnings immediately while the effect of reducing tangible investment is spread over the useful life of the assets. In addition, the benefits associated with innovation are more likely to be delayed than those associated with capital expenditures, and thus are less likely to increase earnings above managers' short-term targets. This difference in accounting treatment and the lag in cash-flows make R&D spending a prime candidate for real earnings management.

These results suggest that managers may decide (*ex post*) to cut investment in innovation to avoid missing an accounting benchmark, even if this means forgoing the benefits of prior investment in innovation. Such a 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 if there is a risk that these projects will be affected by an economic shock (unrelated to the R&D activity). Aghion et al. (2005b) provide a theoretical framework that is largely consistent with this intuition.[6] Empirically, it is also consistent with Graham, Harvey, and Rajgopal (2005) who report that 78% of surveyed executives admit that the accounting effect of an investment would affect their decision to engage in that investment.

Accounting conservatism exacerbates this pressure by encouraging the early recognition of bad news, thus making it more likely that a firm misses some pre-determined targets (e.g., earnings growth). Accounting conservatism thus increases the pressure on managers to meet short-term earnings targets, reduces tolerance of failures, and gives 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, leading to the following main hypothesis:

H: Firms with a greater degree of accounting conservatism are less innovative than those with a lower degree of accounting conservatism.

Although we consider the effect of conservatism on R&D expenditure in Section IV.B, we operationalize our analysis using patents (and patent citations) as the measure of innovation in our baseline specifications. Mansfield (1984) notes that the total R&D figures are hard to interpret because they include a heterogeneous mixture of activities. Specifically, he argues that "long-term projects are mixed up with short-term projects. Projects aimed at small product and

[6] In Aghion et al. (2005b), entrepreneurs can invest in either short-term or long-term productivity-enhancing projects; when financial markets are sufficiently incomplete, long-term investments are disrupted by an (idiosyncratic) shock *ex post*, which reduces entrepreneurs' willingness to engage in long-term investments *ex ante*.

process improvements are mixed up with projects aimed at major new processes and products. Process R&D is mixed up with product R&D."[7] He further adds that "many firms tend to concentrate on short-term, technically safe R&D." For the reasons discussed above, we posit that firms with more conservative accounting focus on development activities associated with small product and process improvements, while their more "liberal" counterparts focus on R&D projects involving major new processes and products. Given the costs associated with obtaining a patent (Horstmann, MacDonald, and Slivinski, 1985),[8] we would expect the former type of R&D activities to generate fewer patents for a given level of R&D expenditure. Consistent with this view, prior literature (e.g., Moser, 2009; de Rassenfosse, 2010) suggests that the propensity to patent (for a given R&D effort) increases with the value of the patent. In essence, firms are more likely to patent an invention when the benefits exceed the costs. To the extent that inventions of conservative firms are less influential than those of "liberal" firms, we further expect the patents of such firms to have a lower impact on citations, future cash flows, and stock prices.

Finally, it should be noted that in our hypothesis, the mechanism through which accounting conservatism affects innovation is the short-term pressure faced by the managers to meet earnings targets or some other forms of managerial myopia. We would thus expect the effect to be more pronounced when the product development cycle is longer, when short-term accounting pressure is greater, or when managers are more myopic. We discuss these testable predictions in greater detail in Section V.B.

[7] Mansfield (1984) also notes that "to answer many important analytical and policy questions, it is essential to disaggregate R&D. Unfortunately, little work has been done on this score."

[8] Aside from legal monetary costs, Horstmann, MacDonald, and Slivinski (1985) stress the economic costs associated with revealing information to the competitors.

III. SAMPLE, VARIABLE DEFINITIONS, AND SUMMARY STATISTICS

A. 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 US patents granted by the US 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. To minimize the potential effect of incomplete coverage, 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 (e.g., Griliches, Pakes, and Hall, 1988). We exclude firms in financial (SIC codes 6000-6999) and utility (SIC codes 4900-4999) industries from the sample (e.g., Atanassov, 2012). Also excluded are firms operating in industries without any registered patents in any year in the entire NBER Patent and Citation Database, although our results are not sensitive to this exclusion. These restrictions result in a final sample of 70,871 firm-year observations between 1976 and 2003.

B. Measures of Innovation

We employ three measures of innovation. The first measure is the number of patents applied for by a firm in a given year (*Patent*). Patent counts, however, imperfectly capture innovation success because patents vary drastically in their technological and economic significance. We therefore follow Hall, Jaffe, and Trajtenberg (2001, 2005) and use forward citations of a patent to measure its quality (importance). However, 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 thus 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 (2001, 2005) provided in the NBER database. We then define *Qcitation* as 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 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. We use *Tcitation* to denote the sum of the adjusted citations during each firm-year under this alternative adjustment approach.

C. Measures of Accounting Conservatism

We use Khan and Watts' (2009) *C_Score* as our baseline measure of accounting conservatism because it is fairly common in the literature and because it provides firm-year estimates. Khan and Watts (2009) show that *C_Score* captures the timing of conservatism changes and the variation of conservatism across firms with different determinants of conservatism, such as the probability of litigation and information asymmetry among investors. A higher value of *C_Score* corresponds to a greater degree of conservatism. However, as any empirical proxy, *C_Score* is potentially subject to measurement errors. Thus, as robustness checks, we follow Patatoukas and Thomas (2011) and consider multiple alternative measures in Section IV.B to mitigate the concern that our results are driven by potential measurement errors. Note that some of these measures are defined at the economy-level and are not subject to cross-sectional variations. This mitigates the risk that our results are driven by firm-specific omitted variables or by firm-specific reverse causality. For the sake of brevity, we define all the conservatism measures in Appendix A1 and describe their results in Section IV.B.

D. Control Variables

To isolate the effect of accounting conservatism on innovation, we control for an array of firm characteristics that have been shown by previous studies to influence innovation. The first control variable is R&D expenses scaled by total assets (*R&D/Assets*), which serves as an important input to innovation (Atanassov, 2013).[9] We also control for firm size measured as the log of total assets, *Ln*(*Assets*). To control for the effect of a firm's life cycle on its innovation ability, we employ *Ln*(*Firm age*), the natural log of firm age, which is the number of years elapsed since a firm enters the CRSP database. Following Hall and Ziedonis (2001), we control for capital intensity measured as the log of property, plant, and equipment divided by the number of employees (*Ln*(*PPE/#Employees*)). Return on assets (*ROA*) is included to capture operating profitability. Also included are *Sales growth* and the market-to-book ratio (*MB*) 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. Chan, Lakonishok, and Sougiannis (2001) show that R&D intensive firms are associated with higher

[9] 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.

stock return volatility. Therefore, we include the standard deviation of daily stock returns over the past fiscal year (*Stock volatility*) as an additional control variable. Since He and Tian (2013) document a negative impact of analyst coverage on innovation, we also control for analyst coverage using the number of analysts making earnings forecast in a given year. Finally, Aghion et al. (2005a) document an inverted-U relationship between product market competition and innovation. Accordingly, we include the Herfindahl index calculated at the three-digit SIC industry (*Herfindahl*) and its squared term (*Herfindahl*^{2}) in the regressions. All control variables are winsorized at the 1% level at both tails of their distributions and measured at t-1 in the regressions. Dollar values are converted into 2000 constant dollars using the GDP deflator.

E. Summary Statistics

Table I presents summary statistics for variables used in the regression analyses. 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. Untabulated results indicate that the autocorrelation of the *C_Score* is 0.5, suggesting that conservatism displays some temporal variation but remains fairly stable for a given firm. Panel B presents descriptive statistics of *C_Score* and the control variables used in the regressions. The statistics are generally consistent with the prior literature (e.g., Atanassov, 2012; Cornaggia et al., 2013).

[INSERT TABLE I ABOUT HERE]

In Panel C we split the sample into five groups according to the value of *C_Score*. Results indicate that the numbers 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 to the least conservative group, the mean number of citations increases from about 8 to 420. The results using *Qcitatio*n and *Tcitation* are similar. In all cases, the difference between the two extreme quintiles is statistically significant with a *p*-value below 0.01. These preliminary univariate results are consistent with our main hypothesis.

[INSERT TABLE II ABOUT HERE]

Table II reports the correlations among *C_Score*, innovation measures, and control variables. 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+*Tcitation*)), 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 0.04. 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, consistent with Mansfield (1984), the relation is relatively modest (correlation coefficients of approximately 0.15). Although interesting, these unconditional relations require more refined multivariate tests, which we turn to next.

IV. MAIN EMPIRICAL RESULTS

A. Baseline Results

We start our multivariate analysis by estimating the following model:

$$Ln(1+Innov_{i,t}) = \alpha + \beta C\_Score_{i,t\text{-}1} + \gamma X_{i,t\text{-}1} + \delta Industry_{i,t} + \theta Year_t + \varepsilon_{i,t}, \qquad (1)$$

where $Innov_{i,t}$ refers to our innovation measures (*Patent*, *Qcitation*, and *Tcitation*) of firm *i* in year *t*. To reduce the skewness of our innovation measures, we use the log of one plus these variables in the regression analyses. We measure *C_Score* at the end of year *t*-1. *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. 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.

We present our baseline results in Table III. 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+*Tcitation*), with *t*-statistics of -5.4, -6.3, and -6.6, respectively. In terms of economic significance, increasing *C_Score* from the 1st quartile (0.04) to the 3rd quartile (0.17) decreases the values of *Patent*, *Qcitation*, and *Tcitation* by 5%, 8%, and 5% from their respective means.[10] The mean Variance Inflation Factor (VIF) is below 2, suggesting that multicollinearity is not an issue in our setting.[11]

[INSERT TABLE III ABOUT HERE]

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 activities innovate more. Firms with more resources (high cash holdings and high *ROA*), higher market-to-book ratio, or greater stock volatility are also more innovative. However, unlike He and Tian (2013), we find that analyst

[10] 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* (-0.306), and then by the mean number of patents (5.71) plus one. It is so because $dLn(1+y)/dx = (dy/dx)/(1+y)$. An increase in *C_Score* from the 1st quartile to the 3rd quartile can be translated into a 0.27 decrease in the number of patents. Given that the average number of patents is 5.71, a decrease of 0.27 patents represents a 5% decrease from the mean value.

[11] The *C_Score* is a fitted value based on size, market-to-book, and leverage, which are also in equation (1). To ensure that the inclusion of the three proxies does not drive our results, we remove *Ln*(*Assets*), *MB,* and *Leverage* from the regression. Our results are not affected.

coverage has a positive effect on the number of patents and citations. In untabulated tests, we are able to replicate their coefficients on analyst coverage if we use their sample period (1993-2005) instead of ours (1976-2003).

B. Robustness Checks

We perform a number of additional tests to ensure that our baseline results are robust to alternative model specifications and different variable definitions.

First, we show our results are robust to alternative measures of conservatism. For the sake of brevity, we only tabulate the coefficients of key variables in Appendix B. Specifically, our results hold when (*A*) using the modified *C_Score* estimated with pre-R&D earnings in Khan and Watts' (2009) model to mitigate the concern that the estimated *C_Score* is influenced by R&D intensity; (*B*) using the modified *C_Score* proposed by Banker et al. (2012) to account for the effect of cost stickiness on conservatism; (*C*) using Basu's (1997) measure; (*D*) using the conservatism measure proposed by Callen, Segal, and Hope (2010); (*E*) using the negative non-operating accruals as an alternative measure of conservatism (as in Givoly and Hayn, 2000 and Ahmed and Duellman, 2007); (*F*) using the modified model of Basu (1997) proposed by Francis and Martin (2010); (*G*) using the modified model of Basu (1997) proposed by Ball, Kothari, and Nikolaev (2013); (*H*) using the model of Ball and Shivakumar (2006). It should be noted that the measures in Panels D and H do not rely on stock market prices, thus are less subject to the concern of inefficient capital markets.

Second, we consider a host of specification checks. For the sake of brevity, we only tabulate the coefficients of key variables in Appendix C. We find that our results hold when (*A*) running negative binomial regressions (instead of OLS regressions) to address the issue that patent and citation counts are non-negative and discrete;[12] (*B*) using *R&D/Assets* as the dependent variable to measure R&D intensity in order to obtain a measure independent of the patent database;[13] (*C*) using as the dependent variable, the average citations per patent (rather than total citations of all patents); (*D*) excluding firm-years with zero patents and citations; (*E*) excluding firms engaging in mergers and acquisitions (identified using the SDC M&A database) in the previous two years and those with acquired R&D and software development costs;[14] (*F*) removing firms with high R&D intensity (defined as firms with a ratio of R&D expenditures to sales greater than 33%) because they may not have significant non-R&D activities (potentially subject to asymmetric accounting treatment) and thus their innovation is less likely to be affected by conservatism. Furthermore, in untabulated tests, we address the potential non-linearity effect or the "scale effect" (i.e., the fact that several independent variables are scaled by total assets but not the dependent variables), and find that our main results are unaffected.[15]

C. Endogeneity

While we document a strong negative association between accounting conservatism and innovation output, the results are potentially subject to two types of endogeneity, omitted

[12] For this test, the dependent variables are the numbers of patents and adjusted citations, rather than their log values.

[13] For this test, we remove R&D from the right hand side of equation (1). The regressions are performed separately for the full sample where we treat missing R&D as zeros, and for the subsample of firms with non-missing R&D. Increasing *C_Score* by one standard deviation reduces R&D intensity by approximately 8%. We obtain similar results when we scale R&D expenditures by sales or by the number of employees (untabulated).

[14] Although in most cases, R&D costs are immediately expensed, there are a limited number of exceptions to this rule (e.g., acquired R&D and software development costs). Thus, to ensure that our results are not affected by the conservative treatment of these assets, we remove firms engaged in M&As and those with software development cost from the analysis.

[15] To ensure that our results are not driven by non-linearity in size, market-to-book ratio, or financial leverage, for each variable we first implement a "quasi Fama-MacBeth" approach by splitting the firms into 20 groups according to each variable, running 20 pooled regressions, and calculating the *t*-statistics using the Fama-MacBeth (1973) approach. Furthermore, we also replace *Ln*(*Assets*) with nine indicator variables that are constructed based on 10 portfolios formed according to *Ln*(*Assets*). To ensure that our results are not driven by the "scale effect", we regress *Innov* on *C_Score* without any additional controls, or use a probit model with the dependent variables being three binary variables that are equal to one if the number of *Patent*, *Qcitation*, or *Tcitation* is greater than zero, and zero otherwise.

variable and reverse causality running from innovation to conservatism. We perform a battery of tests to alleviate these concerns. In performing these tests, we note that the degree of conservatism can be affected by 1) firm-specific factors other than innovation (e.g., the desire to minimize the cost of capital (Garcia Lara, Garcia Osma, and Penalva, 2011) and 2) the need to deal with the constraints coming from the regulatory and litigation environment. These factors provide sources of exogeneity that we exploit below. While all control variables in Table III are still included in the new tests, to save the space, we only report the coefficients on conservatism measures in the tabulated results.

[INSERT TABLE IV ABOUT HERE]

Panels A-F of Table IV show the results from tests that address the issues related to omitted variables. In Panel A, we average all the variables in equation (1) at the firm level and estimate a pure cross-sectional specification (i.e., one observation per firm) to mitigate the concern in time series. We note that the fact that our results hold with Basu's (1997) conservatism measure (Panel C of Appendix B), which is constant across firms in a given year, rules out the possibility that our results are driven by a purely cross-sectional omitted variable. Estimating Basu's (1997) metrics or *C_Score* at the industry-year level does not affect our conclusions (untabulated). In Panels B and C, we include firm and CEO fixed effects in the regressions, respectively, to account for time-invariant omitted firm- and CEO-specific characteristics.[16] In Panel D, we remove the tech bubble (1998-2000) and the post-SOX (2002-2003) periods to mitigate the risk that any regime shifts over these periods affect both innovation and conservatism. In Panel E, we augment equation (1) by including a long list of 16 additional control variables (defined in Appendix A2) that proxy for financial constraints, corporate governance, CEO incentives and

[16] Due to the coverage of *ExecuComp* database, the CEO fixed-effect analysis can only be performed on a small sample with 11,290 observations.

overconfidence, corporate risk-aversion, tax incentives, macroeconomic conditions, and other firm characteristics. The sample shrinks to 6,232 firm-years accordingly. In untabulated tests, we find that results are robust to controlling for an additional set of variables that are also listed in Appendix A2. In Panel F, we use C_Score_{t-4}, instead of C_Score_{t-1}, as the key explanatory variable, because more distantly lagged values of *C_Score* should be less correlated with *current* omitted firm characteristics. Similar results are obtained.

Panels G-K of Table IV show the results from tests that address issues related to reverse causality. We first estimate Basu's (1997) yearly measure of conservatism using only either 1) firms that report no R&D expenses or 2) industries that have no registered patent during the entire sampling period. We then replace *C_Score* with these two modified Basu's (1997) measures in equation (1).[17] The results, reported in Panel G of Table IV, hold. Since this measure is constant across firms per year, the reverse causality would have to come from an aggregate relation at the economy level in time series (running from aggregate innovation to aggregate conservatism). However, since this measure of conservatism is estimated using only non-innovative firms, the relation running from innovation to conservatism cannot be causal. At worst, these results can only be explained by omitted macro-economic variables that affect both conservatism of non-innovative firms and innovation of innovative firms. However, further controlling for the macro-economic conditions in this specification does not alter our conclusion (untabulated).[18]

Second, we include our innovation measures (*Innov*) lagged one period as an additional control to account for the impact of past innovation on conservatism, and find similar results

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[17] Alternatively, we estimate *C_Score* using firms in non-innovative industries (i.e., industries for which the level of *Qcitation* is below the sample median each year (Hirshleifer, Low, and Teoh, 2012)). Results hold.

[18] In particular, we include the NBER recession indicator, the annual GDP growth rates, the aggregate corporate profit growth rates compiled by the Bureau of Economic Analysis, and the stock market returns.

(untabulated).[19] In addition, we use a panel vector autoregressive (PVAR) approach that estimates the following two-equation reduced-form model with the General Method of Moments (GMM) approach.[20]

$$Innov_{i,t} = \alpha_0 + \alpha_1 Innov_{i,t-1} + \alpha_2 C\_Score_{i,t-1} + \alpha_3 Controls_{i,t-1} + f_i + x_t + \varepsilon_{i,t} \quad (2)$$

$$C\_Score_{i,t} = \beta_0 + \beta_1 Innov_{i,t-1} + \beta_2 C\_Score_{i,t-1} + \beta_3 Controls_{i,t-1} + g_i + y_t + \omega_{i,t} \quad (3)$$

The model investigates the causal relation between innovation and conservatism, allowing innovation to affect conservatism over time and vice versa, and accounting for firm fixed effects (*f* and *g*) and time trends (*x* and *y*). The results, reported in Panel H of Table IV, show that the effects of innovation on *C_Score* (i.e., reverse causality) are negative but statistically insignificant, while the negative effect of *C_Score* on innovation remain statistically significant.

Third, we augment Khan and Watts' (2009) model by including the log of the geographical distance between a firm's headquarter and the closest SEC regional office (*Ln*(*Distance*)) as an additional determinant of conservatism. Kedia and Rajgopal (2011) indicate that the SEC is more likely to investigate firms located closer to its offices, suggesting that regulation is most effective when it is local. Since regulation is one of the major determinants of accounting conservatism, we expect that the distance between firm headquarters and the SEC regional offices has a significant and negative impact on accounting conservatism.[21] We do not see an *a priori* reason to expect that closeness to an SEC office would reduce firm innovation. We estimate *C_Score* using *Ln*(*Distance*) as a quasi-instrument. Panel I of Table IV shows that our results still hold.

[19] The only exception is the firm-fixed effect regression using *Ln*(1+*Patent*) as the dependent variable.
[20] The PVAR approach has been used by previous studies (e.g., Grinsten and Michaely, 2005) to investigate the causal effects and intertemporal interactions between endogenous variables. The approach combines the conventional vector autoregression technique, which allows a vector of variables to be endogenously determined in the system, with the panel-data approach, which controls for unobserved heterogeneity.
[21] Consistent with this view, the coefficient (untabulated) on *D*×*R*×*Ln*(*Distance*) has a *t*-statistic of -2.1 in Khan and Watts' (2009) model.

Fourth, we use a change in regulatory regime, 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. Previous research 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. Specifically, Crawford, Price, and Rountree (2010) show that "the asymmetry between the recognition of gains and losses, measured using the Basu (1997) framework, increases in the post-SAB 101 period."[22] Crawford, Price, and Rountree (2010) also note that the enactment of SAB 101 is driven purely by regulatory reasons rather than by the desire to improve the contracting environment.[23] Specifically, we replace *C_Score* in equation (1) with the *SAB 101 indicator* (a binary variable that equals one after the enactment of SAB 101 and zero otherwise) and drop the year indicators from equation (1), while keeping other variables including firm-fixed effects. The results reported in Panel J of Table IV show that the *SAB 101 indicator* is negatively and significantly related to *Ln*(1+*Patent*), *Ln*(1+*Qcitation*), and *Ln*(1+*Tcitation*), suggesting that a positive shock to accounting conservatism causes firms to be less innovative.

In addition, we create an indicator that takes the value of one if the industry in which the firm operates is affected by SAB 101 and zero otherwise (Altamuro, Beatty, and Weber, 2005), and replace *C_Score* with an interaction term between this indicator and the *SAB 101 indicator* in equation (1), while keeping other variables including firm-fixed effects in the regressions.[24] We do this because there may be a concern that *SAB 101 indicator* primarily captures the bursting of

[22] Consistent with this finding, we observe that the correlation coefficient between the *SAB 101 indicator* and *C_Score* is 0.24 in our sample.

[23] Crawford, Price and Rountree (2010) note that "given the contracting benefits of SAB 101 are not clear, *ex post*, the primary benefits of the guidance appear to be related to the reputation of the SEC as a conservative regulatory body protecting the interests of investors."

[24] Since we already control for firm and year fixed effects, the industry and *SAB 101* indicators are not included in these regressions.

the internet bubble. However, Altamuro, Beatty, and Weber (2005) report that the industry affected the most by SAB 101 in their sample is "Pharmaceutical and Chemicals", which is relatively immune to this phenomenon. Untabulated results show that this interaction term is negatively and significantly related to innovation (with *t*-statistics of -2.8, -9.4, and -5.7, respectively).

Finally, we consider intertemporal variations in litigation risk. Basu (1997) indicates that years 1976-1982 and 1983-1990 are low and high legal liability periods, respectively. This change in litigation risk affects accounting conservatism for exogenous reasons. Therefore, we construct an indicator that is equal to one if the year belongs to the 1983-1990 period and zero if the year belongs to 1976-1982. We then replace *C_Score* with this indicator in the regressions. The results reported in Panel K of Table IV show that the coefficient estimates on the indicator variable are significantly negative (*t*-statistics of -5.8, -5.2, and -6.4, respectively). We also estimate the coefficients associated with different yearly indicator variables (after dropping *C_Score* from the regressions) since prior research documents an increase in conservatism over time (e.g., Basu, 1997; Ryan and Zarowin, 2003). The coefficients of yearly indicators become increasingly negative and the effects are statistically significant (untabulated).

To summarize, although endogeneity is a perennial issue that no empirical test can probably entirely rule out, we conduct a large number of tests to mitigate the concerns of omitted variables and reverse causality and find that our results are robust to these concerns. Among them, the results based on conservatism measures estimated with non-innovative firms, lead-lag structures, quasi-instruments, or natural experiments, all suggest that endogeneity does not drive our results. Although each test can be subject to criticism, the totality of evidence points to a causal relation between conditional conservatism and an impediment to innovation.

V. ADDITIONAL TESTS

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

A. Profitability of Innovation

First, we examine whether the degree of conservatism affects the properties of innovation projects. Our argument in Section II suggests that innovation of conservative firms should have a weaker impact on firm profitability and stock prices.

[INSERT TABLE V ABOUT HERE]

We first consider the horizon of the innovative activities. We expect firms with conservative accounting to engage in R&D projects that deliver outcomes faster. To test our prediction, we follow Hilary and Hui (2012) and regress operating cash-flows in year t+1, t+3, and t+5 on the number of patents and citations, controlling for R&D intensity in period t-1, *Ln*(*Assets*), *MB*, *Leverage*, *Beta*, and industry fixed effects.[25] 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 V. For the sake of brevity, the regression estimates for control variables are not reported. As shown in Panels A, B, and C, the coefficient estimates on *Ln*(1+*Patent*), *Ln*(1+*Qcitation*), and *Ln*(1+*Tcitation*) 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 stable.[26] The increase in the magnitude of the coefficients in the low *C_Score* group is statistically significant (with p-values of 0.08, 0.02, and 0.02, respectively) but not in the high *C_Score*

[25] We estimate *Beta* with the Capital Asset Pricing Model (CAPM) using CRSP daily stock returns in each year.
[26] We find, however, that the coefficient estimate on *Ln*(1+*Tcitation*) for the high *C_Score* subsample slightly increases in year t+5 but the increase is statistically insignificant.

group. 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. In addition, even for the first year the point estimates of the coefficients are higher for firms displaying a lower conservatism, suggesting that the patents generated by conservative firms are associated with lower cash-flows. In sum, these results are inconsistent with the view that accounting conservatism leads firms to prune projects with low profitability.

To reinforce this finding, we regress the market reaction to the announcement of patent granting on *C_Score* and the control variables reported in Table III. Untabulated results indicate that *C_Score* is significantly negatively related to the cumulative abnormal return from one day before to one day after the announcement date, *CAR*(-1, 1), with a *t*-statistic of -4.4. Using *CARs* measured over other windows, (-1, 0), (-2, 2), and (-5, 5), does not change the results.[27]

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 accounting conservatism to impede 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 those proposed by Kumar (2009). Specifically, we form a binary variable (*Lottery*) that equals one if the stock return in a given year 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 use a probit model to separately regress *Lottery* on each of

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[27] To estimate *CAR* with the market model using daily stock returns, we use 260 trading days, beginning 390 days and ending 131 days before the patent granting date. We use as the market return the CRSP value-weighted return. Using the CRSP equally-weighted return yields qualitatively similar results.

our three measures of innovation, (*Ln*(1+*Patent*), *Ln*(1+*Qcitation*), and *Ln*(1+*Tcitation*)), controlling for the variables used in equation (1).[28]

[INSERT TABLE VI ABOUT HERE]

Results are presented in Table VI. We find that the coefficient estimates are positive and significant for firms in the low *C_Score* subsample, suggesting that innovation in these firms is associated with a higher likelihood of exhibiting lottery-like features. On the other hand, the coefficient estimates are negative (despite insignificant in most cases) for firms in the high *C_Score* subsample. The coefficient estimates on our three measures of innovation are statistically different across the two subsamples, with a *p*-value of 0.02 or lower in each of the three specifications. Thus, the adverse effect of accounting conservatism on innovations is particularly severe for innovations that generate higher uncertainty but greater upside potentials.

B. Cross-sectional Heterogeneity

To better understand the mechanism through which accounting conservatism affects corporate innovation, we examine whether our results vary across manager-, shareholder-, and other firm-specific characteristics. We also examine whether our results are more evident in industries in which innovation is a more important consideration. As discussed in the hypothesis development section, we expect the results reported in Table III to be more pronounced when the product development cycle is longer, when the accounting performance pressure is greater, or when managers or shareholders have shorter investment horizons.

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.[29]

[28] We exclude *stock volatility* as it is high correlated with the dependent variable.

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).

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 regressions.[30] We then create an indicator to denote 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.[31]

To measure managers' and shareholders' investment horizon, we use 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 middle age CEOs (less than 59); 2) old CEOs (age 59-65), 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

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[29] 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).

[30] We start the sampling period in 1992 because the *ExecuComp* database is not available before 1992.

[31] *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 with *PAPS* between the top 30th and the bottom 30th percentiles of the sample are dropped when we define the *PAPS* indicator.

investors (*STIO*).[32] Specifically, we construct a binary variable (*STIO indicator*) equal to one if in a given year *STIO* is above the top 30th percentile of the sample, and zero if it is below the bottom 30th percentile of the sample.[33] We then include the *STIO indicator* and its interaction with *C_Score* in equation (1) and reestimate it.

To examine whether 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 *Qcitation* per patent is above the sample median across all two-digit SIC industries for a given year. We then reestimate equation (1) by adding an indicator (*InnovInd*) that takes the value of one if the industry is innovative and zero otherwise and its interaction with *C_Score*.

[INSERT TABLE VII ABOUT HERE]

The results are presented in Table VII. The regressions control for the same variables used in equation (1). Again, to save space, we only tabulate the coefficients on the main variables. We find that the results are generally consistent with our expectations. In Panel A, we observe that the effect of conservatism is stronger when the innovation development cycle is around 5 years, and even more so when it is longer than 5 years. In Panel B, we find that the negative effect is exacerbated when CEO compensation is more tied to accounting performance. In Panels C and D, we find that the effect is exacerbated when CEOs approach retirement (59-65 years) and when *transient* institutional ownership is more dominant, respectively. In Panel E, we find that accounting conservatism has a debilitating effect on innovation for firms in innovative industries.

[32] 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).

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

The *t*-statistics for the coefficient estimates on relevant interaction terms in the Table VII regressions range from -2.0 to -14.9. As additional proxies for managerial myopia, we also consider industry homogeneity (Parrino, 1997), CEO ownership (Ma, 2010), and firm transparency (Chowdhury and Fink, 2012). We then interact *C_Score* with high industry homogeneity, low CEO ownership, and low transparency indicators. Untabulated results indicate that the coefficient estimates on all three interactions are negative and significant.[34]

C. *Ex Post* Decision to Cut R&D

Most of our tests so far have taken an *ex ante* perspective by showing that accounting conservatism leads managers to eschew innovative projects. To further show that accounting conservatism induces managers to be more short-term oriented and thus encourages them to invest less in innovative projects, we consider two additional tests.

First, we take an *ex post* view. 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 higher. Following Bushee (1998), we define *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

[34] Specifically, the indicator for high industry homogeneity (low CEO ownership or low transparency) takes the value of one if industry homogeneity (CEO ownership or firm transparency) is above the top (below the bottom) 30th percentile of the distribution each year, and zero if industry homogeneity (CEO ownership or firm transparency) is below the bottom (above the top) 30th percentile of the distribution each year. Industry homogeneity is measured based on the following procedure. First, an equally weighted return index is estimated for each 2-digit SIC industry using firms' monthly stock returns. The monthly return for each firm in each index is then regressed against the equally weighted market return and the equally weighted industry return. The coefficients on the industry return index are then averaged across all firms in each industry to obtain a proxy for the similarity between firms within each industry. CEO ownership is measured as 100 multiplied by the number of CEO stock holdings over the number of shares outstanding. Transparency is the standard deviation of the long-term analyst growth forecast scaled by the mean forecast. The *t*-statistics for the interactions involving the high industry homogeneity indicator are -4.0, -3.0, and -3.3; those for the interactions involving the low ownership indicator are -3.6, -2.5, and -3.0; those for the interactions involving the low transparency indicator are -2.5, -1.9 and -2.3.

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 the prior year's R&D; these firms could eliminate R&D spending but 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 *Cut_R&D* and our key independent variable of interest is *C_Score*. The inclusion of other control variables follows Bushee (1998).[35]

[INSERT TABLE VIII ABOUT HERE]

The results presented in Table VIII indicate 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' 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).

Second, since cutting R&D is costly, firms may prefer to manipulate accruals and resort to cutting R&D only when accrual manipulation becomes difficult. To test this possibility, we form four binary indicators that measure the propensity to manipulate accruals based on Zang (2012) and create an index variable, *Easy*, that measures the easiness to manipulate accruals by

[35] Specifically, we include as controls variables institutional ownership, the change in log R&D per share in prior year, the change in log industry R&D-to-asset ratio (4-digit SIC), the change in log GDP, the change in log capital expenditure per share, the change in log sales per share, the change in log shares outstanding, leverage ratio, free cash flow over current assets, total assets, and *MB*. See Bushee (1998) for detailed definitions of these variables.

summing up these indicators.[36] *Easy* ranges from zero (easy to manipulate accruals) to four (difficult to manipulate accruals). We add this variable and its interaction with *C_Score* in equation (1). Untabulated results indicate that the coefficient estimates on the interaction term are significantly negative, consistent with the notion that firms cut R&D when other options such as accrual manipulations are difficult to implement.

D. Effect of R&D Volatility on Its Productivity

Our main hypothesis is based on the idea that managers who try to maximize firm value but are subject to constraints that force them to cut R&D in response to idiosyncratic shocks will eschew long-term and complex projects. An assumption implicit in our hypothesis is that the timing of the R&D effort is important, and hence the delay in R&D will reduce the productivity of the innovation process. To test the validity of this assumption, we regress *Ln*(1+*Patent*), *Ln*(1+*Qcitation*), and *Ln*(1+*Tcitation*) on R&D volatility (measured as the standard deviation of *R&D/Assets* during the past five years), the level of R&D effort (measured as the average *R&D/Assets* during the past five years), and a vector of control variables used in equation (1) that are also measured as the average over the last five years.[37] Consistent with our intuition, we find that the volatility of the R&D investment has a negative and significant impact on innovation performance. The *t*-statistics of the coefficients on R&D volatility are -9.3, -8.8, and -8.8, respectively. Economically, increasing R&D volatility by one standard deviation (0.05) reduces the values of *Patent*, *Qcitation*, and *Tcitation* by 19%, 28%, and 17%, respectively.

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[36] Specifically, we use the presence of a large auditor, the auditor tenure, the amount of net operating assets, and the length of operating cycle to measure the easiness of accrual manipulation. These variables are defined in greater details in Appendix A3.

[37] Since the analyst following data starts in 1976, the sample period for this test is from 1981 to 2003.

VI. SUMMARY AND CONCLUSION

We examine the impacts of accounting conservatism on corporate innovation. We hypothesize that accounting conservatism curbs innovation through the combination of asymmetric treatment of the non-R&D activities and managerial myopia. Innovative projects tend to take multiple years before delivering positive results (e.g., Holmstrom, 1989). Therefore, if a firm's reporting system and incentive policy put significant pressure on managers to deliver a minimum profitability in every period, managers facing bad news that is unrelated to R&D activities may cut R&D investment when earnings fall short of this minimum requirement. Such a decision would be economically costly but would improve reported earnings in the short run. Realizing that they may have to incur this cost *ex post*, managers may decide *ex ante* to avoid multi-stage long-term innovative projects. Accounting conservatism exacerbates this pressure by making it more likely that firms miss the pre-determined targets. These arguments suggest that firms with a greater degree of accounting conservatism generate a lower level of innovation than firms with a lower degree of accounting conservatism.

Our results are consistent with these arguments. 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 the level of R&D activities. Moreover, the cash-flows generated by innovations in firms with more conservative accounting are lower and have shorter horizons, and these more conservative firms experience less positive market reactions to the announcement of patent granting. The negative effects of accounting conservatism on innovative activities are more pronounced when the industry-level R&D amortizable life is longer, when CEO compensation is more strongly tied to accounting performance, when managers are more likely to be myopic, when firms operate in innovative industries, and when accrual manipulation is more difficult. Overall, these results suggest that accounting conservatism curbs corporate innovation through managerial myopia.

As many empirical studies, ours is also potentially subject to the typical concerns associated with the estimation of empirical proxies. To address the issue of mismeasurement of conservatism and innovation, we use a multiplicity of proxies for these variables. To address the possibility of an omitted variable, we estimate the specifications using a variable that has only time series variation, a pure cross-sectional approach (one observation per firm), and a firm-fixed effect approach. We also control for a long list of potential confounds. To address potential reverse causality and joint determination, we use several approaches. In particular, we estimate the time-series variation of conservatism among non-innovative industries and use this value as a proxy for conservatism among firms that engage in innovative practices. None of these tests affects our conclusion.

Appendix A: Detailed description of variables and models used in supplementary analyses

A1: Alternative models of accounting conservatism

- **Khan and Watts' (2009) *C_Score* (Table III):** *C_Score* is constructed based on Basu's (1997) model as follows. $X_i = \beta_1 + \beta_2 D_i + \beta_3 R_i + \beta_4 D_i R_i + e_i$, 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 when $R < 0$, and zero otherwise. β_4 measures the incremental timeliness for bad news over good news, namely, accounting conservatism. Khan and Watts (2009) assume that both β_3 (*G_Score*) and β_4 (*C_Score*) are linear functions of firm-specific characteristics each year. $\beta_3 = \mu_1 + \mu_2 Ln(E)_i + \mu_3 M/B_i + \mu_4 Lev_i$; $\beta_4 = \lambda_1 + \lambda_2 Ln(E)_i + \lambda_3 M/B_i + \lambda_4 Lev_i$, where $Ln(E)$ 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
$X_i = \beta_1 + \beta_2 D_i + R_i(\mu_1 + \mu_2 Ln(E)_i + \mu_3 M/B_i + \mu_4 Lev_i) + D_i R_i(\lambda_1 + \lambda_2 Ln(E)_i + \lambda_3 M/B_i + \lambda_4 Lev_i) + (\delta_1 Ln(E)_i + \delta_2 M/B_i$
$+\delta_3 Lev_i + \delta_4 D_i Ln(E)_i + \delta_5 D_i M/B_i + \delta_6 D_i Lev_i + \varepsilon_i$, 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 constructed *C_Score*.
- ***C_Score* estimated using pre-R&D earnings (*C_Score_RD* in Panel A of Appendix B):** *C_Score* is re-estimated after adding tax-adjusted R&D expenses back to earnings (X) in Khan and Watts' (2009) model.
- **The modified *C_Score* proposed by Banker et al. (2012) (*C_Score_BBBC* in Panel B of Appendix B):** Banker et al. (2012) modify Khan and Watts' (2009) model by adding a dummy for sale increase and a dummy for sales decrease to account for the confounding effect related to cost stickiness. Our estimation follows equation (6) in Banker et al. (2012).
- **Basu's (1997) measure (*AC_Basu* in Panel C of Appendix B):** The measure is obtained by estimating Basu's model each year across all firms.
- **Callen, Segal, and Hope's (2010) measure (*AC_CSH* in Panel D of Appendix B):** This measure is defined as the ratio of current earnings shocks to earnings news. Current earnings shocks and earnings news are estimated based on a parsimonious vector autoregressive (VAR) model with three state variables consisting of log of stock returns, log of one plus return on equity, and log of book-to-market ratio.
- **Negative non-operating accruals (*NOA* in Panel E of Appendix B):** *NOA* is measured as non-operating accruals divided by the average total assets, which is then averaged over a 3-year periods and multiplied by negative one. Non-operating accruals = (Net income + Depreciation) - Operating cash flows - (*Δ*Accounts receivable + *Δ*Inventories + *Δ*Prepaid expenses - *Δ*Accounts payable – *Δ*Taxes payable).
- **Modified Basu's (1997) model proposed by Francis and Martin (2010) (Panel F of Appendix B):** We add our innovation measures and control for *R&D/Assets* in the model proposed by Francis and Martin (2010). Specifically, we estimate the following model:
$X_{t-1} = \alpha_0 + \alpha_1 D_{t-1} + \alpha_2 R_{t-1} + \alpha_3 D_{t-1} R_{t-1} + \alpha_4 Innov_t + \alpha_5 Innov_t D_{t-1} + \alpha_6 Innov_t R_{t-1} + \alpha_7 Innov_t D_{t-1} R_{t-1} + \alpha_8 R\&D/Assets_{t-1}$
$+\alpha_9 R\&D/Assets_{t-1} D_{t-1} + \alpha_{10} R\&D/Assets_{t-1} R_{t-1} + \alpha_{11} R\&D/Assets_{t-1} D_{t-1} R_{t-1} + Controls_{t-1} + \varepsilon_t$,
where *Innov* represents our innovation measures (*Patent, Qcitation, and Tcitation*). *Controls* include *Ln*(*E*), *MB*, *Lev*, and an indicator for high litigation risk industries and their interactions with D, R and $D \times R$ as well as year and industry fixed effects. We only report in Appendix B the coefficient α_7, which captures the impact of conservatism on innovation.
- **Modified Basu's (1997) model proposed by Ball, Kothari, and Nikolaev (2013) (Panel G of Appendix B):** We adopt Approach 1 of Ball, Kothari, and Nikolaev (2013). The model is similar to that of Francis and Martin (2010) except that *Controls* include *Ln*(*E*), *MB*, *Lev*, *Ln*(*Price*), stock volatilities, and year and industry fixed effects.
- **Ball and Shivakumar's (2006) model (Panel H of Appendix B):** We add our innovation measures and control for *R&D/Assets* in the model proposed by Ball and Shivakumar (2006). Specifically, we estimate the following model:
$ACC_{t-1} = \beta_0 + \beta_1 Neg_{t-1} + \beta_2 \Delta CF_{t-1} + \beta_3 Neg_{t-1} \Delta CF_{t-1} + \beta_4 Innov_t + \beta_5 Innov_t Neg_{t-1} + \beta_6 Inno_t \Delta CF_{t-1} + \beta_7 Innov_t Neg_{t-1} \Delta CF_{t-1}$
$+\beta_8 R\&D/Assets_{t-1} + \beta_9 R\&D/Assets_{t-1} Neg_{t-1} + \beta_{10} R\&D/Assets_{t-1} \Delta CF_{t-1} + \beta_{11} R\&D/Assets_{t-1} Neg_{t-1} \Delta CF_{t-1} + Controls_{t-1} + \varepsilon_t$,
where *Innov* represents our innovation measures (*Patent, Qcitation, and Tcitation*). *Controls* include *Ln*(*E*), *MB*, *Lev*, and an indicator for high litigation risk industries and their interactions with *Neg*, *ΔCF* and *Neg*×*ΔCF* as well as year and industry fixed effects. We only report in Appendix B the coefficient β_7, which captures the impact of conservatism on innovation.

A2: Additional control variables used for Panel E of Table IV.

- **Hadlock and Pierce (2010) index:** $-0.737 \times \text{Size} + 0.043 \times \text{Size}^2 + 0.04 \times \text{Firm age}$.
- **Credit rating:** binary variable that equals one if a firm has Standard & Poor's credit rating on both its long-term debt and short-term debt, and zero others.
- **G-index:** governance index compiled by Gompers, Ishii, and Metrick (2003) from RiskMetrics.
- **CEO delta:** dollar change in CEO stock and option portfolio for 1% change in stock price, in thousands following Core and Guay (2002).
- **CEO vega:** dollar change in CEO option holdings for a 1% change in stock return volatility, in thousands following Core and Guay (2002).
- **CEO overconfidence:** binary variable that equals one for all years after the CEO holds options that are at least 67% in-the-money and zero otherwise.
- **Religiosity:** proportion of religious adherents in a county as in Hilary and Hui (2009).
- **Tax effects:** residual of a regression of marginal tax rate of Graham and Mills (2008) on net income according to Garcia Lara, Garcia Osma, and Penalva (2009).
- **NBER recession dummy:** binary variable that takes a value of one during a NBER recession year, and zero otherwise.
- **Ln(#Segments):** log value of the number of segments of a firm.
- **Timeliness of good news:** *G_Score* estimated by Khan and Watts (2009).
- **Operating leverage:** costs of goods sold divided by selling, general and administrative expenses.
- **Profit margin:** annual net income divided by annual sales.
- **Stock returns:** compounded monthly stock returns over the fiscal year.
- **Litigation risk:** 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 according to Francis, Philbrick, and Schipper (1994).
- **Union:** percentage of workforce in an industry covered by unions according to Hirsch and Macpherson (2003).

Aside from these 16 variables, our results hold if we control for alternative measures of financial constraints such as Kaplan and Zingales' (1997) index, Whited and Wu's (2006) index, or a dividend payer indicator, the market leverage ratio, board size, the percentage of independent directors, the percentage of institutional ownership, operating cash flows scaled by assets, profit margins, the annual GDP growth rates, the aggregate corporate profit growth rates compiled by the Bureau of Economic Analysis, the stock market returns, or the asymmetric sensitivity of R&D to bad news.

A3: Measures for the easiness of accrual manipulation.

- *Easy* is an index that measures the easiness to manipulate accrual-based earnings. The index is constructed as the sum of four indicators: (1) Big8 audit: an indicator that equals one if the firm's auditor is one of the Big 8, and zero otherwise; (2) Audit tenure: an indicator that equals one if the number of years the auditors has audited the client is above 6 years, and zero otherwise; (3) Net operating assets (NOA): an indicator that equals one if a firm's NOA is above the sample median of the corresponding industry-year (3-digit SIC), and zero otherwise; NOA is defined as the shareholders' equity less cash and marketable securities and plus total debt scaled by lagged sales; (4) Operating cycle: an indicator that equals one if a firm's operating cycle is below the sample median of the corresponding industry-year, and zero otherwise. Operating cycle is defined as the days receivable plus the days inventory less the days payable.

Appendix B: Robustness checks on alternative variable definitions

All regressions include the same control variables as those used in Table III, but their coefficients are not tabulated. The detailed definitions for variables and models regarding accounting conservatism are in Appendix A1. 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*): Using *C_Score* adjusted for R&D as an alternative measure of conservatism: N = 70,860			
	Ln(1+*Patent*)	*Ln*(1+*Qcitation*)	*Ln*(1+*Tcitation*)
C_Score_RD	-0.306***	-0.666***	-0.393***
	(-5.4)	(-6.7)	(-6.7)
(*B*): Using the modified *C_Score* proposed by Banker et al. (2012) as an alternative measure of conservatism: N = 70,733			
	Ln(1+*Patent*)	*Ln*(1+*Qcitation*)	*Ln*(1+*Tcitation*)
C_Score_BBBC	-0.168***	-0.268***	-0.203***
	(-4.5)	(-4.0)	(-5.2)
(*C*): Using the Basu's (1997) measure as an alternative measure of conservatism: N = 70,744			
	Ln(1+*Patent*)	*Ln*(1+*Qcitation*)	*Ln*(1+*Tcitation*)
AC_Basu	-0.005***	-0.008***	-0.005***
	(-3.6)	(-3.1)	(-3.6)
(*D*): Using the measure of Callen, Segal, and Hope (2010) an alternative measure of conservatism: N = 69,325			
	Ln(1+*Patent*)	*Ln*(1+*Qcitation*)	*Ln*(1+*Tcitation*)
AC_CSH	-0.007**	-0.014**	-0.009**
	(-2.3)	(-2.1)	(-2.6)
(*E*): Using negative non-operating accruals as an alternative measure of conservatism: N = 51,825			
	Ln(1+*Patent*)	*Ln*(1+*Qcitation*)	*Ln*(1+*Tcitation*)
NOA	-0.254**	-0.428*	-0.254*
	(-2.0)	(-1.8)	(-1.8)
(*F*): Using the modified model of Basu (1997) proposed by Francis and Martin (2010): N = 70,744			
	Innov = *Ln*(1+*Patent*)	*Innov* = *Ln*(1+*Qcitation*)	*Innov* = *Ln*(1+*Tcitation*)
D×*R*×*Innov*	-0.022***	-0.012***	-0.019***
	(-4.0)	(-4.1)	(-3.9)
(*G*): Using the modified model of Basu (1997) proposed by Ball, Kothari, and Nikolaev (2013): N = 70,744			
	Innov = *Ln*(1+*Patent*)	*Innov* = *Ln*(1+*Qcitation*)	*Innov* = *Ln*(1+*Tcitation*)
D×*R*×*Innov*	-0.020***	-0.010***	-0.017***
	(-4.3)	(-3.9)	(-4.1)
(*H*): Using the model of Ball and Shivakumar (2006): N = 69,388			
	Innov = *Ln*(1+*Patent*)	*Innov* = *Ln*(1+*Qcitation*)	*Innov* = *Ln*(1+*Tcitation*)
Neg×*ΔCF*×*Innov*	-0.046***	-0.019**	-0.034**
	(-2.8)	(-2.3)	(-2.3)

Appendix C: Robustness checks on alternative model specifications

All regressions include the same control variables as those used in Table III, but their coefficients are not tabulated. 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 the dependent variables: N = 70,871

	Patent	*Qcitation*	*Tcitation*
C_Score	-0.752***	-1.114***	-1.183***
	(-3.8)	(-4.2)	(-4.9)

(*B*): Using *R&D/Assets* as the dependent variable: N = 70,013 (42,272)

	R&D/Assets (full sample)	*R&D/Assets* (subsample with non-missing R&D)
C_Score	-0.028***	-0.029***
	(-8.0)	(-5.4)

(*C*): Using average citations per patent as dependent variables: N = 70,871

		$Ln(1+\overline{Qcitations})$	$Ln(1+\overline{Tcitations})$
C_Score	-	-0.314***	-0.091***
	-	(-5.6)	(-5.2)

(*D*): Excluding firms with zero patents or zero citations: N_{Patent} = 23,429; $N_{Qcitation, Tcitation}$ = 21,873

	Ln(1+*Patent*)	*Ln*(1+*Qcitation*)	*Ln*(1+*Tcitation*)
C_Score	-0.489***	-0.984***	-0.747***
	(-5.0)	(-6.9)	(-6.4)

(*E*): Excluding firms engaged in M&As and those with acquired R&D and software development cost: N = 44,008

	Ln(1+*Patent*)	*Ln*(1+*Qcitation*)	*Ln*(1+*Tcitation*)
C_Score	-0.300***	-0.567***	-0.374***
	(-5.3)	(-5.5)	(-6.3)

(*F*): Removing firms with higher R&D intensity (*R&D/Sales* > 33%): N = 67,806

	Ln(1+*Patent*)	*Ln*(1+*Qcitation*)	*Ln*(1+*Tcitation*)
C_Score	-0.330***	-0.663***	-0.408***
	(-5.8)	(-6.6)	(-6.9)

References

Acharya, Viral V. and Krishnamurthy V. Subramanian, 2009, Bankruptcy codes and innovation, *Review of Financial Studies* 22, 4949-4988.

Aghion, Philippe, Nick Bloom, Richard Blundell, Rachel Griffith, and Peter Howitt, 2005a, Competition and innovation: An inverted-U relationship, *Quarterly Journal of Economics* 120, 701-728.

Aghion, Philippe, George-Marios Angeletos, Abhijit V. Banerjee, and Kalina Manova, 2005b, Volatility and growth: Credit constraints and productivity-enhancing investment, Working Paper.

Ahmed, Anwer S., and Scott Duellman, 2007, Accounting conservatism and board of director characteristics: An empirical analysis, *Journal of Accounting and Economics* 43, 411-437.

Altamuro, Jennifer, Anne L. Beatty and Joseph Weber, 2005, The effects of accelerated revenue recognition on earnings management and earnings informativeness: Evidence from SEC Staff Accounting Bulletin no. 101, *The Accounting Review* 80, 373-401.

Atanassov, Julian, 2012, Do hostile takeovers stifle innovation? Evidence from antitakeover legislation and corporate patenting, *Journal of Finance*, forthcoming.

Baber, William H., Patricia M. Fairfield, and James A. Haggard, 1991, The effect of concern about reported income on discretionary spending decisions: The case of research and development, *The Accounting Review* 66, 818-829.

Ball, Ray, and Lakshmanan Shivakumar, 2006, Role of accruals in asymmetrically timely gain and loss recognition, *Journal of Accounting Research* 44, 207-242.

Ball, Ray, S.P. Kothari, and Valeri V. Nikolaev, 2013, On estimating conditional conservatism, *The Accounting Review*, forthcoming.

Banker, Rajiv, Sudipta Basu, Dmitri Byzalov, and Janice Y.S. Chen, 2012, Direction of sales change and asymmetric timeliness of earnings, Working Paper.

Basu, Sudipta, 1997, The conservatism principle and the asymmetric timeliness of earnings, *Journal of Accounting and Economics* 24, 3-37.

Bens, Daniel A., Venky Nagar, Douglas J. Skinner, and M.H. Franco Wong, 2003, Employee stock options, EPS dilution, and stock repurchases, *Journal of Accounting and Economics* 36, 51-90.

Biddle, Gary, and Gilles Hilary, 2006, Accounting quality and firm-level capital investment, *The Accounting Review* 81, 963-982.

Biddle, Gary, Gilles Hilary, and Rodrigo Verdi, 2009, How does financial reporting quality relate to investments efficiency?, *Journal of Accounting and Economics* 48, 112-131.

Bolton, Patrick, Jose Scheinkman, and Wei Xiong, 2006, Executive compensation and short-termist behavior in speculative markets, *Review of Economic Studies* 73, 577-610.

Bushee, Brian, 1998, The influence of institutional investors on myopic R&D investment behavior, *The Accounting Review* 73, 305-333.

Callen, Jeffrey L., Dan Segal, Ole-Kristian Hope, 2010, The pricing of conservative accounting and the measurement of conservatism at the firm-year level, *Review of Accounting Studies* 15, 145-178.

Chan, Louis K. C., Josef Lakonishok, and Theodore Sougiannis, 2001, The stock market valuation of research and development expenditures, *Journal of Finance* 56, 2431-2456.

Chemmanur, Thomas J., and Xuan Tian, 2011, Do anti-takeover provisions spur corporate innovation?, Working Paper, Boston College.

Chowdhury, Jaideep and Jason D. Fink, 2012, Managerial myopia: Tests and implications, Working Paper.

Core, John, and Wayne Guay, 2002, Estimating the value of employee stock option portfolios and their sensitivities to price and volatility, *Journal of Accounting Research* 40, 613-630.

Cornaggia, Jess, Yifei Mao, Xuan Tian, and Brian Wolfe, 2013, Does banking competition affect innovation? Working paper.

Crawford, Steven S., Richard A. Price, and Brian R. Rountree, 2010, Regulation and accounting conservatism, Working Paper.

Dechow, Patricia M., and Richard G. Sloan, 1991, Executive incentives and the horizon problem, *Journal of Accounting and Economics* 14, 51-89.

de Rassenfosse, Gaétan, 2010, How much do we know about firms' propensity to patent and should we worry about it?, Working Paper.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607-636.

Francis, Jennifer, Donna Philbrick, and Katherine Schipper, 1994, Shareholder litigation and corporate disclosures, *Journal of Accounting Research* 32, 137-164.

Francis, Jere R., and Xiumin Martin, 2010, Acquisition profitability and timely loss recognition, *Journal of Accounting and Economics* 49, 161-178.

Fudenberg, Drew, and Jean Tirole. 1995, A theory of income and dividend smoothing based on incumbency rents, *Journal of Political Economy* 103, 75-93.

García Osma, Beatriz, Steven Young, 2009, R&D expenditures and earnings targets, *European Accounting Review* 18, 7-32.

García Lara, Juan Manuel, Beatriz García Osma, and Fernando Penalva, 2009, The economic determinants of conditional conservatism, *Journal of Business Finance & Accounting* 36, 336-372.

García Lara, Juan Manuel, Beatriz García Osma, and Fernando Penalva, 2011, Conditional conservatism and cost of capital, *Review of Accounting Studies* 16, 247-271

Givoly, Dan, and Carla Hayn, 2000, The changing time-series properties of earnings, cash flows and accruals: Has financial reporting become more conservative?, *Journal of Accounting and Economics* 29, 287-320.

Gompers, Paul, Joy Ishii, and Andrew Metrick, 2003, Corporate governance and equity prices, *Quarterly Journal of Economics* 118, 107-155.

Graham, John R., and Lillian F. Mills, 2008, Using tax return data to simulate corporate marginal tax rates, *Journal of Accounting and Economics* 46, 366-388.

Graham, John R., Campbell R. Harvey, and Shiva Rajgopal, 2005, The economic implications of corporate financial reporting, *Journal of Accounting and Economics* 40, 3-73.

Griliches, Zvi, Ariel Pakes, and Bronwyn H. Hall, 1988, The value of patents as indicators of inventive activity, NBER Working Paper.

Grinstein, Yaniv and Roni Michaely, 2005, Institutional holdings and payout policy, *Journal of Finance* 60, 1389-1426.

Hadlock, Charles J., and Joshua R. Pierce, 2010, New evidence on measuring financial constraints: Moving beyond the KZ index, *Review of Financial Studies* 23, 1909-1940.

Hall, Bronwyn H., Adam B. Jaffe, and Manuel Trajtenberg, 2001, The NBER patent and citation data file: Lessons, insights and methodological tools, NBER Working Paper.

Hall, Bronwyn H., Adam B. Jaffe, and Manuel Trajtenberg, 2005, Market value and patent citations, *RAND Journal of Economics* 36, 16-38.

Hall, Bronwyn H., and Rosemarie Ham Ziedonis, 2001, The patent paradox revisited: An empirical study of patenting in the U.S. semiconductor industry, 1979-1995, *RAND Journal of Economics* 32, 101-128.

He, Jie, and Xuan Tian, 2013, The dark side of analyst coverage: The case of innovation, *Journal of Financial Economics*, forthcoming.

Hilary, Gilles, and Kai Wai Hui, 2009, Does religion matter in corporate decision making in America?, *Journal of Financial Economics* 93, 455-473.

Hilary, Gilles, and Kai Wai Hui, 2012, Ambiguity aversion, group heterogeneity and corporate investment, Working Paper.

Hirsch, Barry T., and David A. Macpherson, 2003, Union membership and coverage database from the current population survey: Note, *Industrial and Labor Relations Review* 56, 349-354.

Hirshleifer, David A., Angie Low, and Siew Hong Teoh, 2012, Are overconfident CEOs better innovators?, *Journal of Finance* 67, 1457-1498.

Holmstrom, Bengt, 1989, Agency costs and innovation, *Journal of Economic Behavior and Organization* 12, 305-327.

Horstmann, Ignatius, Glenn M. MacDonald and Alan Slivinski, 1985, Patents as information transfer mechanisms: To patent or (maybe) not to patent, *Journal of Political Economy* 93, 837-858.

Kaplan, Steven N., and Luigi Zingales, 1997, Do investment-cash flow sensitivities provide useful measures of financing constraints?, *Quarterly Journal of Economics* 112, 169-215.

Kedia, Simi, and Shiva Rajgopal, 2011, Do the SEC's enforcement preferences affect corporate misconduct?, *Journal of Accounting and Economics* 51, 259-278.

Khan, Mozaffar, and Ross Watts, 2009, Estimation and empirical properties of a firm-year measure of accounting conservatism, *Journal of Accounting and Economics* 48, 132-150.

Kumar, Alok, 2009, Who gambles in the stock market?, *Journal of Finance* 64, 1889-1933.

Leone, Andrew J., Joanna Shuang Wu, and Jerold L. Zimmerman, 2006, Asymmetric sensitivity of CEO cash compensation to stock returns, *Journal of Accounting and Economics* 42, 167-192.

Ma, Tao, 2010, Accounting conservatism and corporate investment, Working Paper.

Mansfield, Edwin, 1984, R&D and innovations: Some empirical findings, *R&D*, *Patents*, *and Productivity*, Editor Zvi Griliches, University of Chicago Press, Chapter 6, 127-154.

Moser, Petra, 2009, Why don't inventors patent?, NBER Working Paper.

Narayanan, M.P., 1985, Managerial incentives for short-term results, *Journal of Finance* 40, 1469-1484.

Narayanan, M.P., 1987, Managerial incentives for short-term results: A reply, *Journal of Finance* 42, 1103-1104.

Noe, Thomas H., and Michael J. Rebello, 1997, Renegotiation, investment horizons and managerial discretion, *Journal of Business* 70, 385- 407.

Patatoukas, Panos and Jacob Thomas, 2013, Comment on "On estimating conditional conservatism" by Ball, Kothari and Nikolaev, Working Paper.

Parrino, Robert, 1997, CEO turnover and outside succession: A cross-sectional analysis, *Journal of Financial Economics* 46, 165-197.

Roychowdhury, Sugata, 2010, Discussion of: "Acquisition profitability and timely loss recognition" by J. Francis and X. Martin, *Journal of Accounting and Economics* 49, 179-183.

Ryan, Stephen G., and Paul Zarowin, 2003, Why has the contemporaneous linear returns-earnings relation declined?, *The Accounting Review* 78, 523-553

Schumpeter, Joseph A., 1947, The creative response in economic history, *Journal of Economic History* 7, 149-159.

Stein, Jeremy, 1988, Takeover threats and managerial myopia, *Journal of Political Economy* 96, 61-80.

von Thadden, Ernst-Ludwig, 1995, Long-term contracts, short-term investment and monitoring, *Review of Economic Studies* 62, 557-575.

Watts, Ross, 2003, Conservatism in accounting, Part I: Explanations and implications, *Accounting Horizons* 17, 207-221.

Whited, Toni M., and Guojun Wu, 2006, Financial constraints risk, *Review of Financial Studies* 19, 531-559.

Yim, Soojin, 2012, The acquisitiveness of youth: CEO age and acquisition behavior, *Journal of Financial Economics*, forthcoming.

Zang, Amy Y., 2012, Evidence on the trade-off between real activities manipulation and accrual based earnings management, *The Accounting Review* 87, 675-703.

Table I. Summary statistics

The sample consists of firm-years covered by both Compustat and the NBER Patent and Citation Database between 1976 and 2003. *C_Score* is Khan and Watts' (2009) measure of accounting conservatism defined in Appendix A1. *Patent* is the number of patents applied for. *Citation* is total number of citations summed across all patents applied by the firm during the year *Qcitation* and *Tcitation* are patent citations adjusted using the weighting index of Hall, Jaffe, and Trajtenberg (2001, 2005) and the method of time-technology class fixed effect, respectively. *R&D/Assets* is R&D expenses scaled by the book value of total assets. *Assets* is the book value of total assets. *Firm age* is the number of years elapsed since a firm enters the CRSP database. *PPE/#employees* is net Property, Plant, and Equipment (*PPE*) scaled by the number of employees. *ROA* is EBITDA/*Assets*. *Sales growth* is the log value of one plus the change in net sales scaled by lagged net sales. *MB* is the ratio of market value of equity over book value of equity. *Cash/Assets* is the cash-to-assets ratio. *Leverage* is (Short-term debt + Long-term debt)/*Assets*. *Stock volatility* is the standard deviation of daily stock returns over the fiscal year. *Analyst coverage* is one plus the number of analysts making earnings forecast in a given 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.

Variables	Mean	Standard Deviation	Q1	Median	Q3
	(1)	(2)	(3)	(4)	(5)
Panel A: Innovation measures					
Patent (*raw*)	5.71	18.13	0.00	0.00	1.00
Citation (*raw*)	107.50	810.56	0.00	0.00	7.00
Qcitation	180.76	1495.95	0.00	0.00	13.17
Tcitation	14.00	99.36	0.00	0.00	1.19
Panel B: Firm characteristics					
C_Score	0.10	0.12	0.04	0.10	0.17
R&D/Assets	0.04	0.08	0.00	0.00	0.05
Assets ($millions)	1,965.78	6,456.80	60.27	213.12	916.16
Firm age (*Years*)	15.69	14.71	5.0	11.0	20.0
PPE/#Employees ($thousands)	112.27	319.40	18.01	32.54	69.05
ROA	0.06	0.18	0.03	0.09	0.14
Sales growth	0.14	0.34	0.00	0.11	0.23
MB	2.86	4.00	1.04	1.73	3.02
Cash/Assets	0.15	0.18	0.02	0.07	0.20
Leverage	0.22	0.18	0.06	0.20	0.34
Stock volatility	0.03	0.02	0.02	0.03	0.04
Analyst coverage	4.86	6.75	0.00	2.00	7.00
Herfindahl	0.20	0.17	0.09	0.14	0.24
Panel C: Mean C_Score and patent/citation counts for different C_Score groups					
C_Score groups	*C_Score*	*Patent*	*Citation*	*Qcitation*	*Tcitation*
Lowest	-0.03	18.89	419.58	735.37	55.64
2	0.04	5.17	64.32	94.14	7.88
3	0.10	2.37	27.18	39.79	3.35
4	0.15	1.42	18.31	24.12	2.14
Highest	0.24	0.70	7.84	9.94	0.96
Lowest - Highest	0.27	18.2	411.7	725.4	54.7
(*p*-value of *t*-test)	(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)

Table II. Pearson correlation matrix

The sample consists of firm-years covered by both Compustat and the NBER Patent and Citation Database between 1976 and 2003. *C_Score* is Khan and Watts' (2009) measure of accounting conservatism defined in Appendix A1. *Patent* is the number of patents applied for. *Qcitation* and *Tcitation* are patent citations adjusted using the weighting index of Hall, Jaffe, and Trajtenberg (2001, 2005) and the method of time-technology class fixed effect, respectively. *R&D/Assets* is R&D expenses scaled by the book value of total assets. *Assets* is the book value of total assets. *Firm age* is the number of years elapsed since a firm enters the CRSP database. *PPE/#employees* is net Property, Plant, and Equipment (*PPE*) scaled by the number of employees. *ROA* is EBITDA/*Assets*. *Sales growth* is the log value of one plus the change in net sales scaled by lagged net sales. *MB* is the ratio of market value of equity over book value of equity. *Cash/Assets* is the cash-to-assets ratio. *Leverage* is (Short-term debt + Long-term debt)/*Assets*. *Stock volatility* is the standard deviation of daily stock returns over the fiscal year. *Analyst coverage* is one plus the number of analysts making earnings forecast in a given 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. Correlations significant at the 5% level are in bold.

Variable	*Ln*(1+ *Patent*)	*Ln*(1+ *Qcitation*)	*Ln*(1+ *Tcitation*)	*C_Score*	*R&D/ Assets*	*Ln*(*PPE/ #Employees*)	*Leverage*	*Cash/Assets*	*Ln*(*Assets*)	*MB*	*Sales growth*	*Stock volatility*	*ROA*	*Ln*(*Analyst coverage*)	*Ln*(*Firm age*)
Ln(1+*Qcitation*)	**0.940**														
Ln(1+*Tcitation*)	**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**									
Cash/Assets	**0.012**	**0.024**	**0.008**	**0.040**	**0.472**	**-0.122**	**-0.442**								
Ln(*Assets*)	**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	**-0.183**	**-0.183**	**-0.181**	**0.395**	**0.329**	**-0.135**	**-0.066**	**0.290**	**-0.486**	**0.174**	**0.040**				
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**			
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**	**0.176**		
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**	**0.187**	**0.246**	
Herfindahl	-0.005	0.004	-0.002	**-0.018**	**-0.152**	**-0.008**	**0.043**	**-0.121**	**0.021**	**-0.057**	**-0.038**	**-0.104**	**0.078**	**-0.046**	**0.087**

Table III. Effect of *C_Score* on innovation outputs

The sample consists of firm-years jointly covered by both Compustat and the NBER Patent and Citation Database between 1976 and 2003. *C_Score* is Khan and Watts' (2009) measure of accounting conservatism defined in Appendix A1. *Patent* is the number of patents applied for. *Qcitation* and *Tcitation* are patent citations adjusted using the weighting index of Hall, Jaffe, and Trajtenberg (2001, 2005) and the method of time-technology class fixed effect, respectively. *R&D/Assets* is R&D expenses scaled by the book value of total assets. *Assets* is the book value of total assets. *Firm age* is the number of years elapsed since a firm enters the CRSP database. *PPE/#employees* is net Property, Plant, and Equipment (*PPE*) scaled by the number of employees. *ROA* is EBITDA/*Assets*. *Sales growth* is the log value of one plus the change in net sales scaled by lagged net sales. *MB* is the ratio of market value of equity over book value of equity. *Cash/Assets* is the cash-to-assets ratio. *Leverage* is (Short-term debt + Long-term debt)/*Assets*. *Stock volatility* is the standard deviation of daily stock returns over the fiscal year. *Analyst coverage* is one plus the number of analysts making earnings forecast in a given year. *Herfindahl* index is computed based on the three-digit SIC code. Constant terms are included but not reported. 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.

		Ln(1+*Patent*)	*Ln*(1+*Qcitation*)	*Ln*(1+*Tcitation*)
	Predicted signs	OLS (1)	OLS (2)	OLS (3)
C_Score	-	-0.306***	-0.635***	-0.390***
		(-5.4)	(-6.3)	(-6.6)
R&D/Assets	+	2.103***	4.087***	2.021***
		(15.4)	(15.9)	(13.6)
Ln(*Assets*)	+	0.296***	0.441***	0.283***
		(21.4)	(21.0)	(19.7)
Ln(*Firm age*)	+	0.140***	0.215***	0.134***
		(10.3)	(9.7)	(9.6)
Ln(*PPE/#Employees*)	+	0.006	0.014	0.006
		(0.5)	(0.6)	(0.5)
ROA	+	0.180***	0.432***	0.193***
		(3.8)	(4.8)	(3.8)
MB	+	0.017***	0.026***	0.017***
		(10.1)	(8.6)	(9.4)
Sales growth	+	0.006	0.037*	0.017
		(0.5)	(1.7)	(1.4)
Leverage	-	-0.395***	-0.673***	-0.394***
		(-7.5)	(-7.4)	(-7.2)
Cash/Assets	+	0.156***	0.347***	0.154***
		(3.1)	(3.7)	(2.8)
Stock volatility	+	4.181***	5.087***	4.376***
		(9.5)	(6.6)	(9.5)
Ln(*Analyst coverage*)	-	0.071***	0.191***	0.096***
		(3.8)	(6.3)	(4.9)
Herfindahl	+	0.144	0.406	0.166
		(0.8)	(1.3)	(0.9)
Herfindahl^2	-	-0.019	-0.181	-0.042
		(-0.1)	(-0.5)	(-0.2)
Industry and year fixed effects		Yes	Yes	Yes
N/ Adjusted R^2		70,871/0.43	70,871/0.40	70,871/0.40

Table IV. Tests for endogeneity

All regressions include the same control variables as those used in Table III, but their coefficients are not tabulated. The detailed definitions for additional control variables in Panel E are defined in Appendix A2. In Panel K, the high litigation risk indicator equals one if the year belongs to the 1983-1990 period and zero if the year belongs to 1976-1982 period. 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	*Ln*(1+*Patent*)	*Ln*(1+*Qcitation*)	*Ln*(1+*Tcitation*)
(*A*): *Estimating a pure cross-sectional specification* (*i.e., one observation per firm*): N = 10,588			
C_Score	-0.475***	-1.458***	-0.665***
	(-5.1)	(-8.3)	(-6.9)
(*B*): *Controlling for firm fixed effects*: N = 70,871			
C_Score	-0.049*	-0.173***	-0.094***
	(-1.7)	(-2.8)	(-2.9)
(*C*): *Controlling for CEO fixed effects*: N = 11,290			
C_Score	-0.302**	-0.560*	-0.290*
	(-2.1)	(-1.8)	(-1.7)
(*D*): *Excluding the tech bubble* (*1998-2000*) *and the post-SOX* (*2002-2003*) *periods*: N = 53,597			
C_Score	-0.338***	-0.581***	-0.394***
	(-5.8)	(-5.6)	(-6.6)
(*E*): *Controlling for additional variables*: N = 6,232			
C_Score	-0.701*	-1.335**	-0.882**
	(-1.8)	(-2.0)	(-2.2)
(*F*): *Using C_Score lagged four years rather than one year*: N = 45,011			
C_Score	-0.148*	-0.265**	-0.184**
	(-2.0)	(-2.0)	(-2.3)
(*G*): *Using conservatism measures estimated with non-innovative firms*			
Basu's (*1997*) *measure using firms that report no R&D expenses*: N = 70,744			
AC_Basu	-0.224***	-0.614***	-0.287***
	(-7.1)	(-9.7)	(-8.3)
Basu's (*1997*) *measure using industries with no registered patent during the entire sample period*: N = 68,778			
AC_Basu	-0.095***	-0.111***	-0.105***
	(-6.5)	(-4.0)	(-6.8)
(*H*): *Using a panel vector autoregressive* (*PVAR*) *approach*: N = 27,655			
Effect of past C_Score on innovation measures (α_2 *in equation* (2))			
$C\_Score_{t\text{-}1}$	-0.092*	-0.321**	-0.168***
	(-1.9)	(-2.8)	(-2.9)
Effect of past innovation measures on C_Score (β_1 *in equation* (3))			
$Innov_{t\text{-}1}$	-0.002	-0.001	-0.002
	(-1.3)	(-1.5)	(-1.3)
(*I*): *Using C_Score instrumented using the distance between firms and SEC regional offices*: N = 58,494			
C_Score	-0.283***	-0.577***	-0.343***
	(-6.1)	(-6.9)	(-7.0)
(*J*): *Using SAB 101 as a natural experiment*: N = 70,871			
SAB 101	-0.052***	-0.414***	-0.117***
	(-3.4)	(-15.5)	(-7.4)
(*K*): *Using an indicator to denote high litigation risk associated with accounting conservatism*: N = 31,681			
High litigation indicator	-0.099***	-0.157***	-0.112***
	(-5.8)	(-5.2)	(-6.4)

Table V. 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 *Tcitation* 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. 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, log value of total assets, the ratio of market equity to book equity, leverage ratio, beta estimated from the CAPM using CRSP daily stock returns in each year, and industry indicators), but for the sake of brevity, the regression estimates for control variables are not reported. 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)
Panel A: Effect of Patent on future operating cash flows				
	A1: Low C_Score subsample			
Ln(1+*Patent*)$_t$	0.009***	0.011***	0.014***	$\chi^2 = 3.13$
	(6.1)	(4.8)	(4.0)	p-value = 0.08
	A2: High C_Score subsample			
Ln(1+*Patent*)$_t$	0.007**	0.005	0.002	$\chi^2 = 0.72$
	(2.2)	(1.0)	(0.2)	p-value = 0.40
Panel B: Effect of Qcitation on future operating cash flows				
	B1: Low C_Score subsample			
Ln(1+*Qcitation*)$_t$	0.005***	0.008***	0.010***	$\chi^2 = 5.16$
	(6.6)	(5.6)	(4.5)	p-value = 0.02
	B2: High C_Score subsample			
Ln(1+*Qcitation*)$_t$	0.003**	0.002	0.002	$\chi^2 = 0.38$
	(2.5)	(0.8)	(0.5)	p-value = 0.54
Panel C: Effect of Tcitation on future operating cash flows				
	C1: Low C_Score subsample			
Ln(1+*Tcitation*)$_t$	0.008***	0.012***	0.015***	$\chi^2 = 5.82$
	(6.2)	(5.6)	(4.4)	p-value = 0.02
	C2: High C_Score subsample			
Ln(1+*Tcitation*)$_t$	0.006*	0.006	0.008	$\chi^2 = 0.10$
	(1.9)	(1.3)	(1.0)	p-value = 0.75

Table VI. Effect of *C_Score* on lottery-like feature of innovation

Firms are divided into high and low *C_Score* groups according to the sample median of *C_Score*. According to Kumar (2009), *Lottery* is a binary variable that equals one if a stock has both above-median idiosyncratic volatilities and above-median idiosyncratic skewness in a given year and zero otherwise. Coefficients are estimated using probit models and capture 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 *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. χ^2 and *p*-values are reported for the tests on equal coefficients for innovative measures between high and low *C_Score* groups.

Dependent variable: *Lottery*	*Low C_Score* (1)	*High C_Score* (2)	*Low C_Score* (3)	*High C_Score* (4)	*Low C_Score* (5)	*High C_Score* (6)
Ln(1+*Patent*)	0.004**	-0.013**				
	(2.2)	(-2.3)				
Ln(1+*Qcitation*)			0.003***	-0.002		
			(2.8)	(-0.9)		
Ln(1+*Tcitation*)					0.005**	-0.005
					(2.6)	(-0.9)
R&D/Assets	0.056*	0.155***	0.053	0.142***	0.056*	0.142***
	(1.7)	(2.8)	(1.6)	(2.6)	(1.7)	(2.6)
Ln(*Assets*)	-0.049***	-0.076***	-0.049***	-0.077***	-0.049***	-0.077***
	(-25.2)	(-19.0)	(-25.9)	(-19.5)	(-25.6)	(-19.4)
Ln(*Firm age*)	-0.022***	-0.049***	-0.022***	-0.049***	-0.022***	-0.049***
	(-8.8)	(-10.0)	(-8.8)	(-10.1)	(-8.8)	(-10.1)
Ln(*PPE/#Employees*)	0.003	-0.014***	0.003	-0.014***	0.003	-0.014***
	(1.4)	(-3.8)	(1.4)	(-3.8)	(1.4)	(-3.8)
ROA	-0.216***	-0.478***	-0.216***	-0.478***	-0.216***	-0.478***
	(-12.0)	(-17.4)	(-12.0)	(-17.4)	(-12.0)	(-17.4)
MB	-0.003***	-0.010***	-0.003***	-0.010***	-0.003***	-0.010***
	(-7.4)	(-9.2)	(-7.4)	(-9.2)	(-7.4)	(-9.2)
Sales growth	0.010*	-0.028***	0.010*	-0.028***	0.010*	-0.028***
	(1.8)	(-3.4)	(1.8)	(-3.4)	(1.8)	(-3.4)
Leverage	0.175***	0.367***	0.175***	0.369***	0.175***	0.369***
	(12.6)	(16.1)	(12.6)	(16.2)	(12.6)	(16.2)
Cash/Assets	0.061***	0.051**	0.060***	0.049**	0.061***	0.049**
	(4.8)	(2.3)	(4.7)	(2.3)	(4.8)	(2.3)
Ln(*Analyst coverage*)	-0.009***	-0.014**	-0.009***	-0.015**	-0.009***	-0.015**
	(-3.5)	(-2.4)	(-3.6)	(-2.5)	(-3.5)	(-2.5)
Herfindahl	-0.136***	-0.281***	-0.135***	-0.281***	-0.135***	-0.281***
	(-3.5)	(-4.4)	(-3.5)	(-4.4)	(-3.5)	(-4.4)
Herfindahl^2	0.129**	0.280***	0.128**	0.279***	0.128**	0.279***
	(2.6)	(3.5)	(2.6)	(3.5)	(2.6)	(3.5)
Sample size/ Pseudo R^2	35,359/0.24	35,373/0.15	35,359/0.24	35,373/0.15	35,359/0.24	35,373/0.15
Test of equal coefficients of innovation measures	χ^2 = 10.95 *p*-value = 0.00		χ^2 = 6.71 *p*-value = 0.01		χ^2 = 5.51 *p*-value = 0.02	

Table VII. Cross-sectional variations in the effect of *C_Score*

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. An industry is classified as a mid (long) R&D cycle industry if its amortizable life is 5 years (longer than 5 years). *PAPS* indicator equals one for high *PAPS* (pay-accounting-performance sensitivity) firms and zero for low *PAPS* firms. 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). *STIO* indicator equals one (zero) for high (low) short-term institutional ownership firms. *InnovInd* equals one if the industry is innovative and zero otherwise. 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	*Ln*(1+*Patent*)	*Ln*(1+*Qcitation*)	*Ln*(1+*Tcitation*)
Panel A: Effect of R&D cycle: N = 70,039			
C_Score	1.201***	1.752***	1.184***
	(10.0)	(8.5)	(9.4)
C_Score × mid R& D cycle indicator	-1.451***	-2.344***	-1.525***
	(-7.6)	(-7.5)	(-7.6)
C_Score × long R&D cycle indicator	-3.056***	-4.767***	-3.172***
	(-14.9)	(-14.5)	(-14.7)
Mid R& D cycle indicator	0.124	0.254	0.164
	(0.8)	(1.0)	(1.0)
Long R&D cycle indicator	0.225	0.262	0.186
	(1.4)	(1.1)	(1.1)
Panel B: Effect of sensitivity of CEO pay to accounting performance: N = 3,252			
C_Score	0.047	-0.264	-0.117
	(0.1)	(-0.3)	(-0.2)
C_Score × *PAPS*	-1.348**	-2.728**	-1.813**
	(-2.0)	(-2.6)	(-2.6)
PAPS	0.103	0.244	0.167
	(0.9)	(1.4)	(1.4)
Panel C: Effect of distance to CEO retirement age: N = 11,258			
C_Score	0.100	0.083	0.068
	(0.2)	(0.1)	(0.1)
C_Score × Young or mid age CEO indicator	-0.875	-1.646	-1.032
	(-1.4)	(-1.6)	(-1.6)
C_Score × Old CEO indicator	-1.674***	-2.615**	-1.666**
	(-2.6)	(-2.4)	(-2.4)
Young or mid-age CEO indicator	0.128	0.224	0.139
	(1.4)	(1.5)	(1.4)
Old CEO indicator	0.263***	0.435***	0.248***
	(2.9)	(2.9)	(2.6)
Panel D: Effect of short-term institutional ownership: N = 37,215			
C_Score	-0.118	-0.315	-0.152
	(-0.9)	(-1.3)	(-1.1)
C_Score × *STIO*	-0.519***	-0.957***	-0.692***
	(-2.8)	(-3.1)	(-3.5)
STIO	-0.039	0.031	-0.002
	(-1.2)	(0.6)	(-0.1)
Panel E: Effect of industry innovation: N = 70,871			
C_Score	0.246*	0.363*	0.340***
	(1.9)	(1.7)	(2.6)
C_Score × *InnovInd*	-0.916***	-1.615***	-1.134***
	(-5.8)	(-6.4)	(-7.1)
InnovInd	0.364***	0.784***	0.454***
	(10.8)	(14.3)	(13.4)

Table VIII. Effect of *C_Score* on Ex Post 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. *Cut R&D* is a binary variable that equals one if R&D per share is cut relative to the prior year and zero otherwise. *Institutional ownership* is the number of shares owned by institutional investors scaled by total shares outstanding from CDA/Spectrum Institutional (13f) Holdings. *Prior ΔR&D* is the change in log value of R&D per share from year *t*-1 to year *t*-2. *ΔIndustry R&D-to-assets ratio* is the change in log value of total R&D expenditures of other firms in the same 4-digit SIC industry scaled by total sales of other firms in the same four-digit SIC industry from year *t* to year *t*-1. *ΔGDP* is the change in log value of GDP from year *t* to year *t*-1. *ΔCapex* is the change in log value of capital expenditure per share from year *t* to year *t*-1. *ΔSales* is the change in log value of sales per share from year *t* to year *t*-1. *ΔNo. of shares outstanding* is the change in log value of total shares outstanding from year *t* to year *t*-1. *Leverage* is (Short-term debt + Long-term debt)/*Assets*. *Free cash flow/Current assets* is (Operating cash flows$_t$ - Average Capex$_{t\text{-}1 \text{ to } t\text{-}3}$)/Current assets$_{t\text{-}1}$. *Assets* is the book value of total assets. *MB* is the ratio of market value of equity over book value of equity. Coefficient are estimated using probit models and capture 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. Year fixed effects are included. 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.

	Dependent variable = Cut R&D		
	SD sample	IN sample	LD sample
	(1)	(2)	(3)
C_Score	0.274**	-0.016	-0.038
	(2.5)	(-0.4)	(-0.9)
Institutional ownership	-0.090**	-0.023	0.002
	(-2.6)	(-1.5)	(0.1)
Prior ΔR&D	0.013	-0.021	0.085***
	(0.3)	(-1.0)	(2.7)
ΔIndustry R&D-to-assets ratio	-0.967*	-0.342	0.349
	(-1.9)	(-1.5)	(1.1)
ΔGDP	1.063	0.158	-0.001
	(1.2)	(0.5)	(-0.0)
ΔCapex	-0.143***	-0.070***	-0.015**
	(-6.5)	(-11.5)	(-2.4)
ΔSales	-0.227***	-0.162***	-0.240***
	(-8.1)	(-15.7)	(-18.3)
ΔNo. of shares outstanding	0.860***	0.176***	0.068***
	(16.7)	(10.2)	(4.4)
Leverage	0.135**	-0.220***	-0.186***
	(2.6)	(-10.5)	(-7.7)
Free cash flow/Current assets	-0.069***	-0.048***	0.027***
	(-3.0)	(-6.2)	(3.2)
Ln(*Assets*)	0.007	-0.011***	0.009***
	(1.3)	(-4.0)	(2.8)
MB	-0.004	0.005***	0.006***
	(-1.6)	(6.1)	(4.7)
Sample size/Pseudo R^2	6,050/0.11	30,060/0.06	22,110/0.08