Internal Information Quality and Firm Innovation

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ABSTRACT: This study investigates how the quality of information available within a firm affects innovation. While higher quality internal information generally improves decision making and task performance, the formal systems that produce higher quality information, such as budgets and internal controls, can paradoxically constrain innovation by limiting managerial discretion. Our empirical results indicate that firms with higher internal information quality generate more patents and patent citations. Cross-sectional analyses show that this positive effect is greater when firms are susceptible to greater internal information frictions due to firm decentralization, short management team tenure, and long product development cycles. We also document that firms experience an increase in innovation following an improvement of internal information quality proxied by internal control weakness remediation. Overall, our results suggest that higher quality internal information promotes innovation by reducing internal information frictions that increase capital allocation uncertainty and impede employee coordination.

Keywords: *internal information quality; innovation; uncertainty; coordination*

JEL Codes: *M41; D8; O32*

1 ǀ INTRODUCTION

Innovation is a key driver of a firm's competitive advantage and a nation's economic growth (Shumpeter, 1983; Porter, 1998). Extensive research in economics and finance has identified how external monitoring devices, such as institutional ownership and takeover pressure, can alter managers' incentive to pursue innovation (e.g., Aghion, Van Reenen, & Zingales, 2013; Atanassov, 2013). In contrast, little attention has been given to the inner workings of firms that can impact innovation success. In this study we characterize innovation as an internal operating challenge that is sensitive to the quality of information available to firm employees. We define internal information quality (IIQ) as the extent to which information is accurately and timely shared within the firm (Demski, 1994; Gallemore & Labro, 2015).

Because innovation is a long-term, complex task with unpredictable outcomes and a high probability of failure, it poses significant challenges to firms with respect to internal capital allocations and employee coordination (Holmstrom, 1989; Hoegl, Weinkauf, & Gemuenden, 2004; Seru, 2014). These challenges are likely to be exacerbated by internal information asymmetries, both vertical and horizontal, among firm managers and employees (Baiman, 1990; Kanodia, 1993). For example, vertical information asymmetries between senior managers and project managers reduce senior managers' willingness to fund innovation because senior managers' are more uncertain about whether project managers have manipulated project reports for their own benefit (Seru, 2014). Horizontal information asymmetries among employees across functional areas, such as R&D, marketing, and manufacturing, reduce innovation outputs by limiting employees' ability to identify team synergies and coordinate their efforts (Souder & Moenaert, 1992; Hoegl et al., 2004; Bushman, Dai, & Zhang, 2016).

We predict that high IIQ firms innovate more because they reduce internal information asymmetries by better collecting, storing and distributing higher quality information within the firm. Firms with higher IIQ reduce vertical information asymmetries by providing senior managers with better information on project costs and benefits and by providing project managers with better information on firms' strategic objectives, resource availability, and project selection criteria (Stein, 1997; Parker & Kyj, 2006). As a result, higher IIQ increases project managers' willingness to propose and senior managers' willingness to fund less conventional, more innovative projects. Firms with higher IIQ reduce horizontal information asymmetries by collecting and transmitting information on team goals, budgets, and performance within and between teams (Shields & Shields, 1998; Edmans, Goldstein, & Zhu, 2011). This distribution of information promotes coordination, an important activity for firms with high R&D intensity, by allowing team members to identify team synergies, monitor team members across functional areas, and more efficiently allocate shared resources (Siegel & Hambrick, 2005; Bushman et al., 2016).

However, the above prediction may not be borne out empirically because higher quality information can have neutral or even negative effects on innovation. One reason is that the formal systems that are needed to increase IIQ, such as budgets and internal controls, can constrain managerial discretion and spontaneity, both of which are essential for performing unstructured, innovative tasks (Amabile, 1998; Bisbe & Otely, 2004; Adler & Chen, 2011). Another reason is that formal information systems, which are designed to produce standardized, 'hard' information, may decrease employees' willingness to share private 'soft' information since formal control systems can reduce employees' intrinsic motivation and trust in upper management (Kramer, 1999; Stein, 2002; Milliken, Morrison, & Hewlin, 2003). Finally, the widespread sharing of information can negatively affect innovation by increasing the likelihood of groups prematurely building consensus or making it easier for employees to freeride on the ideas of others instead of developing their own novel ideas (Janis, 1971; Albanese & Van Fleet, 1985; Esser, 1998; Li & Sandino, 2018).

To empirically investigate the relation between IIQ and innovation, we use measures that capture accessibility, accuracy and timeliness of internal information as developed in prior IIQ-related research (Gallemore & Labro, 2015; Chen, Martin, Roychowdhury, Wang, & Billett, 2018). Our measure of accessibility, which captures the extent to which information is accessible to all managers within a firm, is the absolute difference of profitability from insider trading between top and lower-level managers (Chen et al., 2018). We measure accuracy, which captures how accurately information is generated by internal accounting reporting and budgeting processes, using management earnings forecast accuracy (Dorantes, Li, Peters, & Richardson, 2013). We measure timeliness, which captures how quickly information is processed within a firm, using the number of days that the annual earnings announcement follows fiscal year end (Jennings, Seo, & Tanlu, 2014). In addition, we use a composite measure of IIQ that sums the rankings of all three IIQ characteristics. Following prior innovation research, we measure the quantity and quality of innovation using the number of patents generated by a firm and the number of patent citations received by each patent (e.g., Aghion, Bloom, Blundell, Griffith, & Howitt, 2005; He & Tian, 2013).

Consistent with our predictions, we find that IIQ is significantly and positively associated with patents and patent citations. Specifically, we find that a one standard deviation increase in composite IIQ, measured at year t, is associated with a 9.3% (8.8% and 7.9%) increase in the number of patents in year t+1 (t+2 and t+3). A one standard deviation increase in composite IIQ is associated with an 8.4% (7.1% and 5.8%) increase in the number of citations per patent in year t+1 (t+2 and t+3). Further, we find that our results are robust to controlling for various factors that can affect innovation, including external financial reporting quality, corporate governance, and managerial career risks.

We next perform cross-sectional analysis to investigate whether the positive relation between IIQ and innovation varies with the extent of internal information frictions resulting from high firm decentralization, short tenure of the senior management team and extended product development cycles. We hypothesize that IIQ's effect on innovation will be greater in these settings because managers will more heavily rely on firm-provided information to offset their inability to directly monitor others, identify and leverage team synergies or mitigate the information loss associated with employee turnover (Holmstrom, 1979; Ton & Huckman, 2008). Consistent with our general predictions, we find that the positive relation between IIQ and innovation is more pronounced in these settings where there are likely to be greater internal information asymmetries.[1]

We also exploit the shock to firms' internal information environment caused by the Sarbanes-Oxley Act of 2002 to address the possibility that correlated omitted variables account for our results. We find that compared to firms that do not disclose a material weakness, firms that disclose a Section 404 material weakness experience an increase in the number of patents and citations following the remediation of the internal control weakness. These results are

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[1] We also find that in settings characterized by low decentralization, long senior management team tenure, and short product development cycles, IIQ can have an insignificant or negative effect on innovation. These results are consistent with the argument that formal information systems can impede innovation by constraining managerial discretion and soft information sharing.

consistent with our hypothesis that higher IIQ, as proxied by improved internal controls, is positively associated with innovation.

Our study contributes to several streams of literature. In contrast to prior innovation research that has focused on external governance factors and external reporting quality (Aghion et al., 2013; Atanassov, 2013; He & Tian, 2013; Zhong, 2018, Park, 2018), this study identifies that IIQ, an internal operating characteristic is positively associated with innovation. Our results suggest that higher IIQ increases innovation by reducing internal information asymmetries such as those that are found when business units are geographically disperse, senior manager team tenure is short, and product development cycles are lengthy.

We contribute to the stream of research that identifies how IIQ affects the efficiency of managers' operating decisions. Gallemore and Labro (2015) find that higher IIQ facilitates firm tax planning and reduces effective tax rates. Feng, Li, McVay, and Skaife (2015) document that more effective inventory-related internal control systems improve firm inventory management. Our paper extends this line of research by examining the effect of IIQ on innovation, a less routine type of task that can be negatively affected by the formal information systems that firms often rely upon to promote information quality. Our results show that despite the potentially negative effects of formal information systems, the positive effects of IIQ on managerial decision making extend to less routine, innovative tasks.

Our paper also contributes to the stream of research related to IIQ and firm investment decisions. Goodman et al. (2014) find that management forecast quality is positively associated with the efficiency of corporate acquisitions and capital expenditures. Heitzman and Huang (2018) find that firms with higher IIQ show greater investment sensitivity to internal profit signals than to external price signals. In contrast to these studies that examine how better internal information can help top managers identify investment opportunities and make efficient investment *input* decisions, our study examines how better internal information can, by reducing internal information asymmetries among employees, improve the efficiency of investment process and the resulting *output*. Our study also complements Li, Shu, Tang, and Zheng (2017), who find that internal controls are associated with less investment in R&D in Chinese firms. We complement this study by documenting that internal control weakness remediation by U.S. firms following the passage of the Sarbanes-Oxley Act of 2002 is associated with an increase in firm patents and citations.[2]

Finally, we contribute to research on the effect of information quality on firm investment by identifying alternative mechanisms through which information quality affects investment efficiency. Research in this area has focused on how *external* information quality reduces information asymmetries between insiders and outsiders and improves investment efficiency by reducing financing constraints, enhancing shareholder monitoring and reducing managerial careers concerns (Biddle, Hilary, & Verdi, 2009; Cheng, Dhaliwal, & Zhang, 2013; Zhong, 2018). In contrast, our study finds that higher internal information quality reduces information asymmetries within the firm that can impede innovation by increasing uncertainty related to internal capital allocation decisions and by increasing difficulty for employee coordination.

The remainder of the paper is organized as follows: Section 2 describes the related literature and develops hypotheses; Section 3 describes the sample selection and research design;

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[2] In addition to the difference in the institutional infrastructure of China and U.S., the difference in the types of internal controls examined in our study and Li et al. may account for the difference in our results. We examine the effect of SOX 404 internal control weakness remediation, which pertains to weaknesses of financial reporting. In contrast, Li et al. examine the effect of a composite measure of internal control strength composed of internal control strategies, operating efficiency, reporting quality, legal compliance and safety. The findings of Li et al. suggest that strict controls combined with less efficient governance stifle innovation, consistent with the argument that formal controls can reduce innovation through reduced managerial discretion and soft information sharing.

Section 4 presents our empirical results; Section 5 summarizes the study's main findings and implications.

2 ǀ RELATED LITERATURE AND HYPOTHESES DEVELOPMENT

2.1 ǀ Related literature

Innovation is an economically important activity where firms seek to improve performance by creating and implementing new products, services or operating efficiencies (Schumpeter, 1983; Porter, 1998). Despite the vital role of innovation in increasing firms' long-run competitive advantage (Romer, 1990; Hall, Jaffe, & Trajtenberg, 2005), firms are often reluctant to invest in innovation due to its high degree of uncertainty and probability of failure (Holmstrom, 1989).

Prior research in finance and economics has identified various monitoring mechanisms, often external to the firm, that alter managers' incentive to innovate (Manso, 2011; Aghion et al., 2013). For example, Lerner, Sorensen, and Stromberg (2011) and Aghion et al. (2013) highlight how ownership by private and institutional investors promotes innovation by relieving managers from short-term performance pressure and reducing managers' career risk. Manso (2011) suggests that compensation contracts that tolerate short-term failure and reward long-term success promote innovation. Other studies show that takeover pressure (Atanassov, 2013), analyst coverage (He & Tian, 2013), and stock liquidity (Fang, Tian, & Tice, 2014) also can affect innovation. Recent accounting research explores how external financial reporting quality influences corporate innovation. Zhong (2018) suggests that firm transparency improves innovation by providing shareholders with detailed firm-specific information on managerial actions, which shields managers from undue career risks and disciplines managers into efficient allocation of R&D capital. Park (2018) documents that accruals-based financial reporting quality is positively associated with corporate innovation.

Different from these studies that overlook the inner workings of an organization, our study characterizes innovation as an operating challenge that is prone to internal information asymmetries. These information frictions negatively affect innovation by increasing uncertainty in internal capital allocation and limiting employee coordination, both of which prior research suggests is critical for successful innovation (Holmstrom, 1989; Hoegl et al., 2004; Seru, 2014).

While analytic research suggests that incremental information, even if imperfect, can improve internal operating decisions (e.g., Holmstrom, 1979), it remains an open empirical question whether this relationship applies to innovation. The formal information systems that firms implement to increase information quality, such as budgets and internal controls, may not produce the unique, “soft” information required for innovation (Stein, 2002). Formal information systems can also reduce innovation by decreasing managerial flexibility and intrinsic interest, both of which are important when performing innovative tasks (Amabile, 1998; Bisbe & Otely, 2004; Adler & Chen, 2011). For example, formal control systems can decrease managers’ incentives to innovate and exacerbate the “quite life” agency problem because formal controls impose more objective monitoring and restrict subjective managerial discretion (Li et al., 2017). Finally, a more widespread sharing of information can negatively affect innovation by increasing the likelihood of groupthink or making it easier for employees to freeride on the ideas of others (Janis, 1971; Albanese & Van Fleet, 1985; Esser, 1998; Li & Sandino, 2018).

We next develop hypotheses that predict IIQ’s effect on innovation. Although we recognize that higher IIQ may only have a limited effect on innovation, we draw on theories of information quality to predict that IIQ will positively affect innovation by mitigating internal information asymmetries.

2.2 | Effects of IIQ on innovation

Two challenges that firms must address when engaging in innovation are how to effectively allocate capital for projects that have highly uncertain outcomes and how to coordinate the efforts of employees, who are drawn from different functional areas to perform complex, collaborative tasks. Internal information asymmetries, both vertical and horizontal, exacerbate these two challenges (Baiman, 1990; Kanodia, 1993). We argue that firms that have higher IIQ are likely to innovate more because these firms have policies and procedures in place that promote the collection, storage, and distribution of more accurate and timely information.

Vertical information asymmetries exist between different levels of management and impede innovation by increasing uncertainty related to capital allocation decisions. For example, project managers contribute to vertical information asymmetries when they exploit their superior local knowledge to manipulate reports to upper management to increase project funding and obtain perquisites (Baiman, 1990; Seru, 2014). The prospect of this behavior motivates senior managers to ration capital, a strategy that leads to underinvestment in otherwise profitable projects (e.g., Antel & Eppen, 1985; Harris & Raviv, 1996). Senior managers contribute to vertical information asymmetries when they ambiguously define project managers' roles and distort information in order to hide their preferential funding of pet projects or disproportionately support affiliated project managers (Parker & Kyj, 2006; Duchin & Sosyura, 2013). Faced with ambiguously defined roles and unclear project selection criteria, project managers respond by proposing projects that are less novel, have more certain cash flows, and are more difficult to reject based on their objective merits.

Horizontal information asymmetries exist within teams at all levels inside the firm and decrease innovation by impeding coordination, a critical factor for innovation success. Horizontal information asymmetries occur when project teams are composed of specialists, drawn from different functional areas, who lack a common technical language and shared understanding of the project's objectives (Souder & Moenaert, 1992; Hoegl et al., 2004). Horizontal information asymmetries also result from innovation's extended development cycles in which employee turnover is likely to occur and information exchange is interrupted (Holmstrom, 1989). These horizontal information asymmetries negatively affect innovation because they prevent team members from engaging in interdependent problem solving and developing team synergies (Winter, 2010; Edmans et al., 2011; Bushman et al., 2016).

We argue that firms that have higher IIQ innovate more because higher quality information, achieved through practices such as participative budgets, cost allocation procedures, strategy maps, and knowledge management systems, reduces internal information asymmetries that create uncertainty and impede coordination.[3] High IIQ firms reduce vertical information asymmetries by providing senior managers with better information on project costs and benefits and by giving project managers a clearer understanding of the firm's strategic objectives, resource availability and project selection criteria (Shields & Shields, 1998; Parker & Kyj, 2006; Seru, 2014). By reducing vertical information asymmetries and the associated uncertainty, higher IIQ increases the willingness of project managers to propose and senior managers to fund more novel, innovative projects (Seru, 2014). High IIQ firms reduce horizontal information

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[3] As described in our Measures of Internal Information Quality section below, our measures of information quality consist of information accessibility, accuracy, and timeliness. We use these measures of information quality since prior research has identified their importance in internal management decision making and often link these measures to the internal processes that reduce information asymmetries such as participatory budgets and quality circles (Shields & Young, 1993; Parker & Kyj, 2006). We also use these measures to be consistent with prior IIQ research (Gallemore & Labro 2014; Chen et al. (2018).

asymmetries by transmitting information on team goals, budgets, and performance across functional areas within individual teams and between teams collaborating on the same task (Shields & Shields, 1998; Fisher, Maines, Peffer, & Sprinkle, 2002; Horngren, Datar, & Rajan. 2012). As a result, higher IIQ enables team members to better coordinate the use of shared resources, engage in more effective interdependent problem solving, and leverage team competencies, which are essential for performing complex, innovative tasks (Hoegl et al., 2004; Siegel & Hambrick, 2005; Bushman et al., 2016).

Because firms with higher IIQ can reduce internal information asymmetries that impede innovation, we predict the following:

H1: Internal information quality is positively associated with innovation.

2.3 | Cross-sectional effects of IIQ on innovation

To explain the mechanisms underlying the effect of IIQ on innovation, we propose cross-sectional predictions that exploit variation in internal information frictions due to decentralization, short management team tenure, and extended product development cycles. We expect a stronger effect of IIQ in these settings because when these organizational characteristics reduce employees' ability to observe or interact with others, employees will more intensively use the firm-provided information system to reduce internal information asymmetries (e.g., Holmstrom 1979; Ton & Huckman, 2008).

Decentralized firms, characterized by multiple business or geographic segments, are susceptible to internal information asymmetries that impede innovation. Decentralized firms are prone to vertical information asymmetries because decentralization prevents senior managers at headquarters from directly monitoring the actions of project managers and prevents project managers from having direct access to relevant firm information available at headquarters

(Baiman, 1990; Parker & Kyj, 2006; Seru, 2014). Decentralized firms are also vulnerable to horizontal information asymmetries since industry diversification and geographic distance impede information exchange, resource sharing, and mutual monitoring across different segments (Holmstrom, 1982; Carpenter & Sanders, 2004; Seru, 2014).

Short senior management team tenure also increases internal information asymmetries. Shorter team tenure contributes to vertical information asymmetries since senior management teams with short tenures have less opportunity to exchange information with project managers related to ongoing projects and new initiatives (Parker & Kyj, 2006). Senior management teams with shorter tenures are vulnerable to horizontal information asymmetries because these managers have less interaction with one another and are less likely to identify complementary competencies and develop team synergies that are required for innovation (Siegel & Hambrick, 2005; Bushman et al., 2016).

Finally, projects that take place over extended, multi-stage development cycles, a common characteristic of innovation, contribute to internal information asymmetries (Holmstrom, 1989). Longer product development cycles exacerbate vertical information asymmetries because senior manager are less able to discern manipulations in reports for projects whose costs and benefits will not be known with certainty until the distant future (Baiman, 1990; Horngren, 2012).[4] Longer product development cycles exacerbate horizontal information asymmetries since extended development periods increase the risk of job rotation and employee

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[4] Project managers are particularly likely to conceal unfavorable information from senior managers when there is an extended development cycle because as the length of the cycle increases the risk of project funding being reallocated also increases (Holmstrom, 1989; Brusco & Panunzi, 2005).

turnover, which disrupts information flow among employees and creates knowledge gaps (Shaw, Duffy, Johnson, & Lockhart, 2005).[5]

Since managers and employees who cannot directly monitor or interact with others are likely to place greater reliance on available internal information to overcome the detrimental effect of internal information asymmetries on innovations, we predict the following:

> *H2: The positive association between internal information quality and innovation is more pronounced when firms are prone to greater internal information asymmetries.*

3 | VARIABLE MEASURES, SAMPLE SELECTION, AND RESEARCH DESIGN

3.1 | Measures of innovation

Following the recent economics and finance literature (Aghion et al., 2005; He & Tian, 2013), we construct two measures of a firm's innovation productivity. The first measure is a firm's total number of patent applications filed in a given year that are eventually granted. We use a patent's application year instead of its grant year because the application year is superior in capturing the actual time of innovation development (e.g., Griliches, Pakes, & Hall, 1988). Patent counts, however, do not precisely capture the quality of innovation as patents vary greatly in their technological and economic impact. To better assess a patent's quality, we construct the second measure of firm innovation productivity by counting the total number of non-self-citations each patent receives in subsequent years. Therefore, our first measure captures a firm's overall innovation productivity and the second measure captures the significance and quality of its innovation output.

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[5] Innovation is particularly vulnerable to the negative effects of turnover because it is a non-standardized, knowledge-based task that relies on the discretion of individual employees as opposed to the structure of standardized policies and procedures (Ton & Huckman, 2008).

We adjust these raw measures of innovation outputs to address the truncation problems arising from the finite length of the sample. It takes an average of two years for a patent application to be granted and patents receive citations over extended periods of time (e.g., 50 years). Therefore, patents applications that are filed *before* the end of our sample period but granted *after* the end of the sample period are omitted. Granted patents have less time to accumulate citations in the later years of our sample. We address this truncation bias by multiplying the yearly patent and citation counts by the weighting factors calculated in Hall, Jaffe, and Trajtenberg (2001).[6] Because both patents and patent citations are right-skewed, we use natural logarithm of patents and citations per patent. To avoid losing firm-year observations with zero patents or citations, we add one to the actual values when calculating the variables.

3.2 | Measures of internal information quality

Following Gallemore and Labro (2014) and Chen et al. (2018), we use publicly observable instruments to measure the accessibility, accuracy, and timeliness of internal information. Our first measure is the absolute difference in insider trading profitability between top managers and lower-level managers, multiplied by negative one.[7, 8] We adopt this measure because prior studies have used the difference in the trading profits of two parties to infer the differences in their private information sets and have provided extensive validation of the measure (Ravina & Sapienza, 2010; Wang, Shin, & Francis, 2012; Chen et al., 2018). This perspective is also consistent with the budgeting literature since differences in trading profits is

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[6] The annual weighting factors for patent and citation counts are estimated using the historical distribution of these measures.

[7] Consistent with Chen et al. (2018), top managers include chairman, vice chairman, CEO, CFO and COO. Lower-level managers include divisional officers, officers of subsidiary companies, and other non-executive officers such as vice presidents, and senior vice presidents. See Appendix A for detailed variable definitions.

[8] We multiply our individual IIQ measure by negative one so that a higher value indicates higher internal information quality.

likely to reflect the extent to which subordinates reveal private information to their superiors through formal mechanisms such as participatory budgets (e.g., Parker & Kyj, 2006). The average insider trading return for each type of manager is calculated as the average cumulative market-adjusted abnormal return within 180 trading days from the transaction date for all open market insider trades made by the managers during the most recent three fiscal years. For open market sale transactions, the return is multiplied by negative one.

The second measure is management forecast accuracy, calculated as the average of absolute earnings forecast error over the past three years, scaled by lagged share price and multiplied by negative one. Although management forecast accuracy has been used as a measure of external reporting quality, it can also be used as a proxy for the quality of the internal reporting system. For example, Cassar and Gibson (2008) use survey data to document that the preparation of internal reports is associated with more accurate revenue forecasts, particularly for firms operating in uncertain environments. Dorantes et al. (2013) find that the implementation of enterprise systems, which are designed to promote the exchange of information across business functions within a firm, is associated with increased management forecast accuracy. Our use of an information accuracy measure is also consistent with prior management accounting research that has identified the importance of information accuracy on internal decision making and how firms can use practices such as participative budgets and quality circles to collect accurate information about local operating conditions (e.g., Shields & Young, 1993).

The third measure is timeliness of earnings announcement, calculated as the number of days between the end of the fiscal year and the earnings announcement date, divided by 365 and multiplied by negative one. Consistent with prior IIQ research, we use this measure as a proxy for information quality since higher quality internal information systems are better equipped to more quickly gather internal information from different sources and complete end-of-period closings (Gallemore & Labro, 2014; Jennings et al., 2014). This effect is likely to be particularly pronounced for firms that have relied on external consultants to improve their internal information system and have automated how information is gathered (Gallemore & Labro, 2014). The importance of information timeliness on internal management decisions, such as capital budgets, is underscored by prior management accounting research which has identified information timeliness as an important information characteristic in internal decision-making settings (e.g., Larker, 1981).

In addition, we use a composite measure that sums the decile rankings of our measures for managerial differential returns, guidance accuracy and earnings announcement timeliness. We first rank the decile of each IIQ proxy from 1 to 10 and then sum the rankings of the three individual IIQ proxies and divided the sum by 30 to form the composite ranking.[9]

We use these publicly observable proxies for IIQ for two reasons. One reason is that prior research suggests that these proxies capture internal information quality (e.g., Cassar & Gibson, 2008; Jennings et al., 2014; Chen et al., 2018). Another reason is that these proxies allow us to overcome data availability constraints associated with internal firm data and increase the generalizability of our results to a broader sample (Gallemore & Labro, 2015). Since these proxies may also reflect external reporting quality, we explore the cross-sectional variation in the severity of internal information frictions and our analysis suggests that higher IIQ promotes innovation by easing information frictions between parties inside the firm.

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[9] If managerial differential return or guidance accuracy is missing for a firm year, its ranking is replaced by that of earnings announcement timeliness, which allows us to retain as many firm years as possible to increase the generalizability of our results. In our robustness test, we require that all three measures are available and our results are inferentially identical.

3.3 | Sample selection

We construct the innovation variables using the latest version of the National Bureau of Economic Research (NBER) database and the Google Patents and Citations dataset.[10] We use earnings announcement dates on Compustat and IBES to compute earnings announcement timeliness, management forecast data on First Call to compute management forecast accuracy, and insider trading data on Thomson Financial to compute differential insider trading profit for top and lower-level managers. Finally, we obtain financial accounting and segment data from Compustat, stock market data from CRSP, and institutional holding data from Thomson Financial to construct our control and cross-sectional variables.

Our sample period spans from 1984 to 2009. We begin our sample period in 1984 when earnings announcements dates are available in IBES and Compustat. We end our sample period in 2009 because 2010 is the last year with available innovation data and we examine the relation between current IIQ and one-year ahead innovation. For a firm-year observation to enter our sample, it has to have non-missing data for each control variable and at least one IIQ proxy. Timeliness of earnings announcement is available throughout the entire time period (1984–2009), whereas management forecast accuracy and insider trading return difference are available from 1994 to 2009 and 1996 to 2009, respectively. Our composite measure is computed from 1996 to 2009 as 1996 is the first year all three measures are available.

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[10] The NBER database was developed by Hall et al. (2001) and contains detailed patent and citation information from 1976 to 2006. It is the primary source of data for studies in the innovation literature. The Google Patents and Citations dataset spans from 1926 to 2010 and it was constructed by Kogan, Papanikolaou, Seru, and Stoffman (2012). The data is publicly available on Professor Stoffman's academic website: hiips://iu.app.box.com/v/patents. We rely on the NBER for data until year 2004 and supplement it with data from the Google dataset for the period 2005 to 2010. We end the usage of the NBER data in 2004 to mitigate the truncation bias discussed above.

3.4 | Research design

To test our main hypothesis that internal information quality is positively associated with innovation outputs, we estimate the following regression model:

$$\begin{array}{ll} LogPatent_{i,t+n} & = \beta_0 + \beta_1\, IIQ_{i,t} + \beta_2\, LogSIZE_{\,i,t} + \beta_3 TobinQ_{i,t} + \beta_4\, ROA_{i,t} + \beta_5\, LEV_{i,t} \;+ \\ (LogCitePat_{i,t+n}) & \beta_6\, R\&D_{i,t} + \beta_7\, CAPEX_{i,t} + \beta_8\, PPE_{i,t} + \beta_9\, STDEARN_{i,t} + \beta_{10}\, LogAGE_{i,t} \;+ \\ & \beta_{11}\, HHI_{i,t} + \beta_{12}\, HHI^2_{i,t} + \sum Year + \sum Industry + \varepsilon_{i,t} \end{array} \qquad (1)$$

where *i* indexes firm, *t* indexes time, and *n* equals one, two or three. Firm innovation is proxied by two measures – patents and citations. *LogPatent* equals the natural logarithm of one plus the number of patents the firm filed during the fiscal year (and eventually granted), and *LogCitePat* is natural logarithm of one plus the number of citations received per patent. To account for the long-term nature of innovation process, we test the lead-lag relation between IIQ and *LogPatent* (*LogCitePat*) up to three years ahead. For brevity, we only report results on the one-year-ahead test in our cross-sectional analyses.

IIQ is internal information quality proxied by the four measures discussed earlier. They are absolute differential returns between top and lower level managers (*DRET*), management earnings forecast accuracy (*MACC*), timeliness of earnings announcement (*TIME*), and a composite measure (*COMPOSIT*) that consists of the three individual measures.

Following prior research in finance and economics (Aghion et al., 2013; Hirshleifer, Low, & Teoh, 2012; He & Tian, 2013), we control for other firm characteristics that may impact both innovation and internal information quality. We include the natural log of total sales (*LogSIZE*) as a proxy for firm size since larger firms may have more resources to invest in innovation. We include Tobin's Q (*TobinQ*) as proxy for investment opportunities. We include return on assets (*ROA*) as a proxy for firm operating performance because more profitable firms are more likely to have funds to invest in innovative projects. We include leverage (*LEV*) to account for the effect of capital structure on innovation since firms facing greater financial constraints and solvency risks, due to high debt levels, are less likely to invest in innovation.

We control for R&D expense scaled by total assets (*R&D*) because it serves as an important input to innovation and allows us to capture the variation in innovation output given the same input. Thus, we expect a positive relation between R&D expense and innovation output. We also control for capital expenditure (*CAPEX*) as various firm investment activities can be significantly correlated. We control for capital intensity (*PPE*) because capital intensive firms may place less reliance on investment in intangible assets.

Further, we include earnings volatility (*STDEARN*) to proxy for firms' innate business environments, as firms operating in more uncertain environment may have greater need to compete and innovate. We include the natural logarithm of firm age (*LogAGE*) to control for the effect of a firm's life cycle on its innovation ability. Finally, Aghion et al. (2005) document an inverted-U relationship between product market competition and innovation. Accordingly, we include the Herfindahl-Hirschman Index (*HHI*) calculated at the two-digit SIC industry and its squared term (HHI^2) in the regressions. To minimize the effect of outliers, we winsorize all continuous variables at the 1st and 99th percentiles. We include year fixed effects to control for time-specific trends in innovation and industry fixed effects based on Fama-French 12 industry classification to account for industry heterogeneity in innovation in all our models. More detailed definitions of our variables are presented in Appendix A.

To better understand the mechanism through which IIQ affects corporate innovation, we examine the cross-sectional variation of the effect of IIQ. To test our hypothesis that the positive relation between IIQ and innovation is greater when firms are more susceptible to internal information asymmetry problems, we estimate the following regression models:

$$\begin{aligned} LogPatent_{i,t+n} \quad &= \beta_0 + \beta_1\, IIQ_{i,t} + \beta_2\, HDCENTR_{i,t} + \beta_3\, IIQ \times HDCENTR_{i,t} + \sum Controls_{i,t} \\ (LogCitePat_{i,t+n}) \quad & \quad + \sum Year + \sum Industry + \varepsilon_{i,t} \end{aligned} \tag{2a}$$

$$\begin{aligned} LogPatent_{i,t+n} \quad &= \beta_0 + \beta_1\, IIQ_{i,t} + \beta_2\, STTENURE_{i,t} + \beta_3\, IIQ \times STTENURE_{i,t} + \sum Controls_{i,t} \\ (LogCitePat_{i,t+n}) \quad & \quad + \sum Year + \sum Industry + \varepsilon_{i,t} \end{aligned} \tag{2b}$$

$$\begin{aligned} LogPatent_{i,t+n} \quad &= \beta_0 + \beta_1\, IIQ_{i,t} + \beta_2\, LPCYCLE_{i,t} + \beta_3\, IIQ \times LPCYCLE_{i,t} + \sum Controls_{i,t} \\ (LogCitePat_{i,t+n}) \quad & \quad + \sum Year + \sum Industry + \varepsilon_{i,t} \end{aligned} \tag{2c}$$

where *HDCENTR, STTENURE* and *LPCYCLE* are proxies for information frictions. *HDCENTR* is high firm decentralization, an indicator variable that equals one if the annual decile ranking of a firm's business diversification is above the median and geographic dispersion is above the median, zero otherwise. We calculate business diversification (geographic dispersion) by summing the squares of the ratio of firm sales in each business (geographic) segment to total firm sales.

STTENURE is short team tenure, an indicator variable that equals one if the duration of a firm's top management team tenure is in the lowest quintile of our sample, zero otherwise. Team tenure is measured as the number of consecutive years that the senior management team remains unchanged. The count restarts at zero when two or more of the original team members leave the team. Top management team consists of the top executives whose compensation information is available on the Standard and Poor's Execucomp database. Generally, these executives include CEO, CFO, COO, chairman, president, and vice president.

LPDCYCLE is long product development cycle, an indicator variable that equals one if the commercial life of the products that emerge from an industry's R&D has an amortization period of five years or longer, and zero otherwise. We use the industry-level R&D amortizable life to proxy for the length of product development cycle because products that have longer development cycles generally have longer amortizable lives (Chang, Hilary, Kang, & Zhang, 2015). For example, consumer non-durables, which have short commercial lives, have development cycles of about 12 months while consumer durables and manufacturing, which have longer commercial lives, have lengthier development cycles of 36 to 50 months (Griffin 1997). [11]

4 | EMPIRICAL RESULTS

4.1 | Descriptive statistics

Table 1 presents descriptive statistics for the variables used in our main analysis. Panel A of Table 1 shows that on average, a firm in our sample has 5.8 granted patents per year and each patent receives 3.4 non-self-citations. The mean and median value of *DRET* are -0.21 and -0.12, respectively, indicating that the absolute difference in insider trading profitability between top and lower-level managers has a mean (median) value of 21% (12%). The mean and median value of *MACC* are -0.03 and -0.01, respectively, indicating that in our sample management earnings forecast error has a mean of 3% and a median of 1% of share price. The mean (median) value of *TIME* is -0.12 (-0.11), corresponding to 43.8 (40.1) days of lag between earnings announcement date and fiscal year end. Our composite measure of internal information quality has a mean of 0.58 and a median of 0.60. Regarding other variables, an average firm has annual sales of $2.41 billion, Tobin's Q of 1.82, ROA of 8.8%, and leverage of 21.5%. It has an average R&D-to-assets ratio of 4.1%, capital expenditure-to-assets of 5.8%, PPE-to-assets ratio of 27.2% and is about 16.9 years old.

Panel B of Table 1 presents Pearson correlations between variables used in our main analyses. *LogPatent* and *LogPatCite* are positively correlated with *TIME*, consistent with timely

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[11] The data on amortizable lives are available on Professor Aswath Damodaran's website (http://people.stern.nyu.edu/adamodar/New_Home_Page/spreadsh.htm). Following Chang et al. (2015), we use five years as the cut off period to define long life cycle.

processing of information increasing innovations. However, *LogPatent* and *LogPatCite* are not positively correlated with *MACC* or *DRET*, which is likely caused by the correlations of both innovation and IIQ with other firm characteristics. This result suggests that it is necessary to control for other determinants of firm innovation. The three individual proxies of IIQ are positively and significantly correlated with each other and have correlations ranging from 0.08 to 0.13, suggesting that these proxies capture the overlapping underlying construct but represent distinct aspects of IIQ. In addition, both innovation and internal information quality measures are significantly correlated with most of the other variables, suggesting that it is necessary to include these variables as controls.

Table 2 reports the average number of patents and citations per patent by the Fama-French 12 industries. In our sample, firms with patents are spread across all industries. The average number of patents filed by a firm in a year ranges from a high of 18.65 for the Chemicals industry to a low of 0.08 for the Utilities industry. The average number of citations each patent receives in a year ranges from a high of 6.49 for the Business Equipment industry to a low of 0.29 for the Finance industry.

4.2 | Main results

Table 3 reports results on our main hypothesis test (H1). Each panel reports the effect of each of our IIQ proxies on patents and patent citations in the next three years. Panel A shows that differential insider trading return between top and lower-level managers (*DRET*) is positively and significantly related to both measures of innovation in all three future years with t-statistics ranging from 1.87 to 3.04. One standard deviation increase in *DRET* increases the values of one-year ahead patents and patent citations by 1.7% and 1.2%, respectively. Panel B shows that management forecast accuracy (*MACC*) is positively and significantly related to both measures of innovation in all three future years with t-statistics ranging from 1.86 to 3.01. One standard deviation increase in *MACC* increases the values of one-year ahead patents and patent citations by 2.0% and 2.1%, respectively. Panel C shows that timeliness of earnings announcement (*TIME*) is positively and significantly related to both measures of innovation in all three future years with t-statistics ranging from 6.68 to 11.02. In terms of economic significance, a one standard deviation increase in *TIME* increases the values of one-year ahead patents and patent citations by 6.6% and 7.4% from their respective means.

Panel D shows that our composite measure of IIQ is positively and significantly related to both measures of innovation in all three future years with t-statistics ranging from 10.08 to 12.4. In terms of economic significance, one standard deviation increase in *COMPOSIT* increases the values of one-year ahead patents and patent citations by 9.3% and 8.4% from their respective means. Relative to the coefficients on the three IIQ proxies, the coefficients on *COMPOSIT* have higher t-values and greater economic significance, consistent with innovation being affected by multiple dimensions of IIQ.

With regard to control variables, most of the coefficients have the expected signs. For example, firms that are larger, more profitable, have greater growth opportunities and lower leverage produce more innovation outputs. Firms that engage in more R&D and capital investments innovate more. Finally, firms that are less capital intensive and more mature produce more innovation.

4.3 | Cross-sectional Results

Table 4 reports our results on whether the effect of IIQ on innovation is greater when internal information frictions are higher (H2). For brevity, we report only the coefficients on the IIQ, proxies for information frictions and the interaction terms. Panel A reports results from regressions in which the level of firm decentralization is used as a proxy for information friction.

We find that the interaction between *IIQ* and *HDCENTR* is positive and significant in seven out of eight regressions with t-statistics ranging from 2.67 to 10.78, indicating that the positive relation between IIQ and innovation is stronger when firms are more decentralized. We also find that the coefficient on *IIQ* is insignificant in five out of eight regressions, consistent with IIQ having a neutral effect on innovation in firms with low decentralization.

Panel B reports results from regressions in which top management team tenure is used as a proxy for information frictions. We find that the interaction between *IIQ* and *STTENURE* is positive and significant in six out of eight regressions with t-statistics ranging from 1.84 to 3.64, indicating that the positive relation between IIQ and innovation is generally more pronounced when senior management team tenure is short. The coefficient on *IIQ* is insignificant in four out of eight regressions, indicating that IIQ may have neutral effect on innovation when senior management team tenure is long.

Panel C reports results from regressions in which the length of product development cycle is used as a proxy for information frictions. We find that the interaction between *IIQ* and *LPDCYCLE* is positive and significant in all regressions with t-statistics ranging from 2.03 to 16.28, indicating that positive relation between IIQ and innovation is more pronounced when product development cycle is long. The coefficient on *IIQ* is significantly negative in six out of eight regressions, consistent with IIQ having a negative effect on innovation when product development cycle is short.[12]

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[12] In some cross-sectional tests, the coefficients on *HDCENTR*, *STTENURE* and *LPDCYCLE* change from positive to negative when the IIQ proxy changes from the individual IIQ measures to the composite measure. The change is caused by the differences in the distributions of the IIQ measures as reported in Panel A of Table 1. For example, the means of *DRET*, *MACC* and *TIME* are -0.21, -0.03 and -0.12, respectively, whereas the mean of *COMPOSIT* is 0.58. When we demean all the IIQ proxies, we find that the coefficient on *HDCENTR and LPDCYCLE (STTENURE)* are significantly positive (insignificant) across all specifications.

Overall, the cross-sectional results are consistent with our prediction that the effect of IIQ is magnified when there is higher information frictions within an organization. They provide evidence that the effect of IIQ on innovation is through reducing information asymmetries between parties insider the firm. Further, the results show that IIQ has neutral or negative effects on innovation when internal information frictions are less severe. These results are consistent with the argument that in these settings, the cost of formal information systems in constraining manage discretion and soft information sharing offsets or outweighs the benefit of formal information systems in providing high quality standardized, hard information in promoting innovation.

4.4 | Internal control weakness remediation

Our results above suggest that IIQ positively affects innovation. However, our IIQ proxies could be related to other firm and manager characteristics that may be the real drivers of innovation. To address this concern, we perform a difference-in-differences analysis of the shock to firms' internal information environment caused by the Sarbanes-Oxley Act of 2002. We use this shock since firms that disclosed a Section 404 material weakness in 2004 and subsequently remediated it are likely to have improved their IIQ (e.g., Feng, Li, & McVay, 2009). Using the following difference-in-differences (DiD) model, we examine whether internal control weakness remediation increases innovation:

$$\begin{aligned} &LogPatent_{i,t+n} &&= \beta_0 + \beta_1 MW_{i,t} + \beta_2 POST_{i,t} + \beta_3 MW\times POST_{i,t} + \textstyle\sum Controls_{i,t} + \sum Industry \\ &(LogCitePat_{i,t+n}) &&\quad + \varepsilon_{i,t} \qquad (3) \end{aligned}$$

MW is an indicator variable that equals one if the firm initially disclosed a Section 404 material weakness in 2004 but remedied it immediately (i.e., the firm did not disclose a Section 404 material weakness after 2004), zero if the firm did not disclose any material weakness. The sample contains firm-years observations three years before and after the event year. Specifically, *POST* is an indicator variable equal to one if the fiscal year is in 2005, 2006 or 2007, and zero if the fiscal year is in 2001, 2002 or 2003. *MW×POST* is the interaction of the two variables. Table 5 reports our results from the DiD analysis. We find that the coefficient on the interaction term is positive and statistically significant for both *LogPatent* (0.093, t = 1.97) and *LogCitePat* (0.114, t = 1.93). The result suggests that compared with firms that did not disclose material weakness, firms that disclosed material weakness experience a 9.7% and 12.1% increase in the number and quality of patents after they remediated their internal control weakness.

4.5 | Additional Controls

We incorporate additional control variables in our analysis to address the concern that the relation between innovation and IIQ is driven by factors that are correlated with both. First, we control for accruals quality as accruals quality and IIQ are likely positively correlated and prior research shows that external reporting quality affects firm innovation through reduced information asymmetry between shareholders and managers (Zhong, 2018; Park, 2018). Second, we control for proxies for corporate governance, managerial career risk and managerial ability that can impact innovation and IIQ, including transient and dedicated institutional ownership, analyst following, stock liquidity, takeover pressure, managerial ownership, and CEO’s total compensation (Aghion et al., 2013; Atanassov, 2013; He & Tian, 2013; Fang et al., 2014).[13] Third, we control for stock return, stock return volatility, cash flow volatility, and analyst forecast dispersion as both innovation and IIQ can be significantly related to firm performance and operating environment.

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[13] Following Gallemore and Labro (2015), we include the natural logarithm of the CEO's total compensation to control for managerial ability.

Table 6 reports results from regressions with additional controls. Columns (1) and (2) show that shows that *IIQ* continues to load positively and significantly when accruals quality proxy estimated from the Dechow and Dichev (2002) model is included. In addition, Consistent with Zhong (2018) and Park (2018), accruals quality is positively associated with innovation. Our results are similar when we proxy for accruals quality using unsigned discretionary accruals estimated from the Jones (1991) model. Columns (3)-(4) show that the coefficients on *IIQ* remain positive and significant although including all the additional controls reduces our sample size substantially.

The coefficients on the other control variables generally have the expected signs. For example, the negative coefficients on transient investor ownership and stock liquidity are consistent with short-term performance pressure reducing innovation (Fang et al., 2014). The positive efficient on takeover pressure is consistent with takeover pressure reducing managerial slack (Atanassov, 2013). The negative coefficients on managerial ownership is consistent with managerial ownership discouraging managerial risk taking. Consistent with Guo, Pérez-Castrillo, and Toldrà-Simats (2019), we find that analyst coverage is positively associated with innovation.

The overall results suggest that internal information quality has an important and distinct effect on innovation beyond external reporting quality and external corporate governance examined in prior research.

4.6 | Alternative Model Specifications

Following prior literature (e.g., He & Tian, 2013; Fang et al., 2014), we use pooled OLS regression in our main analysis. To account for the nonnegative nature of patents and citations and the fact that a nontrivial fraction of sample firms with patent and citation counts equal to zero, we perform additional tests using a Tobit model. To account for the discrete nature of patents, we estimate negative binominal regressions in which we use the raw values of the patent count and citation per patent as the dependent variable. Panel A of Table 7 reports that when the Tobit model is used, our composite measure of IIQ (*COMPOSIT*) is positively and significantly related to both measures of innovation in all three future years with t-statistics ranging from 10.74 to 11.9. Panel B of Table 7 shows that when the negative binomial model is used, *COMPOSIT* is positively and significantly related to the count of patent and citation per patent in all three future years with z-statistics ranging from 4.08 to 7.46.

5 | CONCLUSIONS

This paper investigates the effects of internal information quality on innovation. We find that firms with higher IIQ generate more patents and patent citations despite the possible negative effects that formal information systems can have on innovation. We also find that the effect of IIQ is stronger when firms have greater internal information frictions, due to greater firm decentralization, shorter team tenures for senior managers, and longer product development cycles. Our difference-in-differences analysis of the shock to firms' internal information environment caused by the passage of the Sarbanes-Oxley Act indicates that innovation increases after improvements are made to firms' internal controls. Collectively, these results suggest that IIQ improves innovation by reducing internal capital allocation uncertainty and facilitating employee coordination.

Our study contributes to several streams of research. It contributes to the innovation literature by identifying that IIQ affects both the quantity and quality of innovation. This perspective, which characterizes innovation as an internal operating challenge that is sensitive to internal information asymmetries, is in contrast to prior research that focuses on the effects of corporate governance and managerial incentives on innovation (e.g., Manso, 2011).

We also complement the emerging literature on how IIQ affects managers' operating decisions. While prior research finds that higher internal information quality facilitates operating decisions, such as tax planning and inventory management (e.g., Gallemore & Labro, 2015; Feng et al., 2015), innovation research implies that formal information systems and strong controls, which are needed to produce higher information quality, can negatively affect creativity and innovation (Amabile, 1998; Bisbe & Otely, 2004; Adler & Chen, 2011). Our findings suggest that the positive effects of IIQ on managerial decision making can be extended to non-routine, less structured tasks, such as innovation.

Finally, our study contributes to the research stream related to how information quality affects investment efficiency. Prior research suggests that higher information quality can reduce external information asymmetry between managers and investors and improve investment by reducing agency costs and financing constraints (e.g., Biddle et al., 2009; Cheng et al., 2013; Zhong, 2018). In contrast we show that higher information quality can reduce internal information asymmetries within firms and improve innovation success by reducing capital allocation uncertainty and improving employee coordination.

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APPENDIX A

Variable definitions

Innovation measures:	
LogPatent	Natural logarithm of one plus total number of patents filed (and eventually granted) in fiscal year t+n.
LogCitePat	Natural logarithm of one plus total number of citations received on the firm’s patents filed and eventually granted, scaled by the total number of the patents in fiscal year t+n.
Internal information quality measures:	
DRET	Accessibility, measured as the absolute difference of average insider trading profitability between top managers and lower-level managers during the prior three fiscal years and multiplied by -1. The average insider trading profitability is calculated as the average cumulative market-adjusted abnormal return within 180 trading days per transaction. For open market sale transactions, the return is multiplied by -1. Top managers include chairman, vice chairman, CEO, CFO and COO. Lower-level managers include those managers with relationship code of "OX", "OS", "AV", "EVP", "O", "OP", "OT", "S", "SVP", "VP", "GP", "LP", "M", "MD", "OE", or "TR".
MACC	Management forecast accuracy, measured as the average management earnings forecast accuracy over the prior three fiscal years. Management forecast accuracy is the absolute value of management estimate of EPS minus actual EPS divided by lagged share price and multiplied by -1.
TIME	Timeliness of earnings announcement, measured as the number of days between the end of the fiscal year and the firm's earnings announcement, divided by 365 and multiplied by -1.
COMPOSIT	Composite measure of internal information quality, measured as the sum of the decile rankings of timeliness, accuracy, and accessibility. Specifically, we first decile rank each of the internal information quality proxies (ranged from 1 to 10). Then we sum the rankings of the proxies and divide the sum by 30 to form the composite ranking. If accuracy or accessibility is missing for a firm-year, its ranking is replaced by that of timeliness.
Firm characteristics:	
LogSIZE	Firm size, measured as the natural logarithm of one plus firm sales [sale].
TobinQ	Market-to-book ratio during fiscal year t, calculated as market value of equity (prcc_f × csho), plus book value of assets (at), minus book value of equity (ceq), minus balance sheet deferred taxes (txdb), scaled by book value of assets (at).
ROA	Return-on-assets ratio, defined as operating income before depreciation (oibdp) scaled by book value of total assets (at).

LEV	Leverage, measured as the book value of debt [dltt +dlc] divided by the sum of debt and equity [dltt+dlc+ceq+pstk].
R&D	Research and development expenditures (xrd) scaled by total assets (at).
CAPEX	Capital expenditures (capx) scaled by total assets (at).
PPE	Property, plant & equipment (ppe) scaled by total assets (at).
STDEARN	Earnings volatility, measured as the standard deviation of EPS over the prior 12 quarters, with a minimum of four quarters available.
LogAGE	Firm age, measured as the natural log of one plus the number of years the company has appeared on Compustat.
HHI	Herfindahl-Hirschman Index of 4-digit SIC industry *j* in which firm *i* belongs, using sales as the measure of market share.

Cross-sectional variables:

HDECENTR	High firm decentralization, an indicator variable that equals one if a firm's rankings of business diversification and geographic dispersion are both above median in that year, zero otherwise. Business diversification (Geographic dispersion) is measured as sum of the squares of firm sales in each business (geographic) segment divided by total firm sales.
STTENURE	Short team tenure, an indicator variable that equals one if the duration of a firm's top management team tenure is in the lowest quintile of the sample, zero otherwise. Team tenure is measured as the number of consecutive years the top managers management team stays the same. The count restarts at zero when two or more of the original team members leave the team. Top management team consists of the top executives whose compensation information is available from Standard and Poors' Execucomp database. These executives generally include CEO, CFO, COO, chairman, president, and vice president.
LPDCYCLE	Long product development cycle, an indicator variable that equals one if the commercial life of the products emerge from R&D in the industry has an amortization period of five years or longer, and zero otherwise. Product development cycle is measured as the commercial life of the products emerge from R&D in the industry. We obtain the information on amortizable lives from professor Aswath Damodaran's website (hiip://people.stern.nyu.edu/adamodar/New_Home_Page/spreadsh.htm).

Additional control variables:

AQ	Accruals quality estimated using the Dechow and Dichev (2002) measure, as adjusted by McNichols (2002) and Francis, LaFond, Olsson, and Schipper (2005).

INST_TRAN	Transient institutional ownership, calculated as total number of shares owned by transient institutional investors divided by total number of shares outstanding.
INST_DEDI	Dedicated institutional ownership, calculated as total number of shares owned by dedicated institutional investors divided by total number of shares outstanding.
NUMA	Number of analysts, defined as the average number of analysts following the firm during the fiscal year.
LIQ	Stock liquidity, measured as relative effective spread, i.e., the absolute value of the difference between the execution price and the midpoint of the prevailing bid-ask quote (effective spread) divided by the midpoint of the prevailing bid-ask quote.
TAKEOVER	Takeover pressure, estimated by calculating the predicted value of *Target* from the following logit regression based on Cremers, Nair, and John (2009): $Target_{i,t+1} = \beta_0 + \beta_1 Q_{i,t} + \beta_2 PPE_{i,t} + \beta_3 Cash_{i,t} + \beta_4 LogMV_{i,t} + \beta_5 Leverage_{i,t} + \beta_6 ROA_{i,t} + \beta_7 Block_{i,t} + \beta_8 IndMA_{i,t} + Year + \varepsilon_{i,t}$ where *Target* is an indicator variable that is equal to one if a firm is a takeover target in that year, zero otherwise. *Q* is market to book ratio of the firm value; *PPE* is asset structure measured by the property, plant, and equipment to assets ratio; *Cash* is the cash and short-term investments to assets ratio; *LogMV* is log value of market equity; *Leverage* is book debt to assets ratio; *ROA* is return on assets; *Block* is an indicator variable that is equal to one when an institutional blockholder exists, zero otherwise; *IndMA* is an indicator variable that is equal to one when a takeover attempt occurred in the same industry in the year prior to the acquisition. *Year* indicates year dummies. All continuous variables are industry mean-adjusted based on four-digit SIC codes.
EXEC_OWN	Executive ownership, measured as the sum of shares owned by top five executives scaled by the number of shares outstanding
EXEC_COMP	Executive compensation, measured as the natural logarithm of CEO’s total compensation in the fiscal year.
RET	Stock return, measured as the buy and hold return over the fiscal year.
STDRET	Return volatility, measured as the standard deviation of monthly stock returns over the past 12 months.
STDCFO	Cash flow volatility, defined as the standard deviation of operating cash flow over the past four years.
AFDISP	Analyst forecast dispersion, calculated as the average standard deviation of analysts’ forecasts during the fiscal year.

APPENDIX B

Measuring innovation

Consistent with prior studies, we rely on the National Bureau of Economic Research (NBER) database as our primary source for the innovation data. The database contains all patent filings from 1976 to 2006 that were eventually granted by the patent office. While the average lag between the filing and grant dates is about two years, it can be as long as six years. The lag creates a truncation bias in the data since many patent applications filed in the last few years were still under review and had not been granted (and therefore unrecorded) by 2006. We minimize the truncation bias by adjusting the count of patents for the period 2001 to 2006 using the weights presented in Hall, Jaffe, and Trajtenberg (2001). The adjustment can be characterized by the following equation:

$$Patent_{Adjusted} = \frac{Patent_{unadjusted}}{\sum_{s=0}^{2006-t} w_s}$$

where $Patent_{unadjusted}$ is the unadjusted number of patent applications at year *t* from 2001 to 2006. *Ws* is the application-grant lag distribution – the percentage of patents applied for in a given year that are granted in *s* years.

We also extend our sample period to 2010 using a secondary data source – Google Patent and Citations, which spans from 1926 to 2010. Because the last two years (2005 and 2006) in the NBER dataset are most subject to the truncation bias, we replace them with data from the Google dataset. We adjust the last six years of patent count in the Google dataset using the same adjustment weights.

The truncation bias also applies to the citation counts since a patent can keep receiving citations beyond the end of the sample period. Following Hall, Jaffe, and Trajtenberg (2001), we correct for this truncation bias by scaling up the citation counts using the variable "*hjtwt*" provided by the NBER patent database, which is calculated based on the shape of the citation lag distribution.

TABLE 1 Descriptive statistics

Panel A: Descriptive Statistics

Variable	**N**	**Mean**	**Stdev**	**10%**	**25%**	**50%**	**75%**	**90%**
Innovation Measures:								
Patent	87,902	5.759	26.201	0.000	0.000	0.000	1.000	7.000
CitePat	87,902	3.404	9.411	0.000	0.000	0.000	0.000	12.295
Internal Information Quality Measures:								
DRET	46,061	-0.210	0.258	-0.512	-0.271	-0.120	-0.046	-0.016
MACC	20,436	-0.030	0.083	-0.061	-0.023	-0.009	-0.004	-0.001
TIME	87,902	-0.122	0.054	-0.197	-0.151	-0.112	-0.079	-0.060
COMPOSIT	67,531	0.582	0.227	0.267	0.400	0.600	0.767	0.900
Firm Characteristics:								
SIZE	87,902	2,410	7,468	31	91	333	1,328	5,142
TobinQ	87,902	1.818	1.413	0.924	1.045	1.326	2.014	3.260
ROA	87,902	0.088	0.161	-0.034	0.038	0.111	0.169	0.231
LEV	87,902	0.215	0.188	0.000	0.042	0.187	0.341	0.476
R&D	87,902	0.041	0.089	0.000	0.000	0.000	0.042	0.133
CAPEX	87,902	0.058	0.063	0.002	0.016	0.040	0.077	0.131
PPE	87,902	0.272	0.246	0.017	0.068	0.197	0.415	0.677
STDEARN	87,902	0.396	0.576	0.061	0.108	0.211	0.437	0.869
AGE	87,902	16.9	13.7	4.0	6.0	12.0	25.0	39.0
HHI	87,902	0.206	0.182	0.037	0.072	0.156	0.277	0.451
HHI^2	87,902	0.075	0.138	0.001	0.005	0.024	0.077	0.203

Panel B: Correlations

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	*LogPatent*																
2	*LogCitePat*	**0.73**															
3	*DRET*	**0.04**	**0.00**														
4	*MACC*	**-0.02**	**-0.03**	**0.09**													
5	*TIME*	**0.18**	**0.13**	**0.13**	**0.08**												
6	*COMPOSIT*	**0.16**	**0.12**	**0.49**	**0.37**	**0.85**											
7	*LogSIZE*	**0.26**	**0.07**	**0.23**	**0.21**	**0.31**	**0.29**										
8	*TobinQ*	**0.12**	**0.14**	**-0.10**	**-0.08**	**0.05**	**0.02**	**-0.19**									
9	*ROA*	**0.04**	**0.01**	**0.13**	**0.34**	**0.18**	**0.20**	**0.41**	**-0.03**								
10	*LEV*	**-0.07**	**-0.10**	**0.02**	**0.12**	**-0.13**	**-0.08**	**0.22**	**-0.27**	**0.07**							
11	*R&D*	**0.21**	**0.24**	**-0.12**	**-0.32**	**-0.02**	**-0.09**	**-0.39**	**0.34**	**-0.56**	**-0.28**						
12	*CAPEX*	**0.02**	**0.03**	**-0.03**	0.00	**-0.07**	**-0.08**	**-0.02**	**0.06**	**0.15**	**0.10**	**-0.04**					
13	*PPE*	**-0.02**	**-0.04**	**0.04**	**0.12**	**-0.03**	**-0.05**	**0.18**	**-0.15**	**0.22**	**0.34**	**-0.21**	**0.60**				
14	*STDEARN*	**0.08**	**0.02**	**-0.02**	**-0.31**	**-0.02**	**-0.06**	**0.20**	**-0.11**	**-0.09**	**0.12**	**-0.01**	**-0.02**	**0.05**			
15	*LogAGE*	**0.22**	**0.12**	**0.18**	**0.17**	**0.19**	**0.19**	**0.49**	**-0.16**	**0.18**	**0.12**	**-0.19**	**-0.06**	**0.20**	**0.08**		
16	*HHI*	**0.06**	**0.03**	0.00	**0.04**	**-0.08**	-0.10	**0.04**	**0.01**	**0.07**	**0.05**	**-0.07**	**-0.01**	**-0.03**	**-0.01**	**0.03**	
17	HHI^2	**0.04**	**0.02**	**0.01**	**0.04**	**-0.06**	**-0.07**	**0.04**	0.00	**0.07**	**0.05**	**-0.07**	0.00	**-0.01**	**-0.02**	**0.04**	**0.93**

Panel A reports descriptive statistics. Panel B reports Pearson correlations. *Patent* is the number of patents. *CitePat* is the number of citations per patent. *DRET* is the absolute difference of insider trading returns between top and lower-level managers. *MACC* is management forecast accuracy. *TIME* is timeliness of earnings announcement. *COMPOSIT* is the composite measure of the three internal information quality proxies. *SIZE* is firm sales in millions. *TobinQ* is market-to-book value. *ROA* is return on assets. *LEV* is leverage. *R&D* is research and development expenditures scaled by assets. *CAPEX* is capital expenditure scaled by assets. *PPE* is property, plant, and equipment scaled by assets. *STDEARN* is standard deviation of earnings. *AGE* is firm age. *HHI* is Herfindahl-Hirschman Index. HHI^2 is the square of the Herfindahl-Hirschman Index. Detailed definitions of all variables are provided in Appendix. Bolded correlation coefficients are significant at the 10 percent level.

TABLE 2 Descriptive statistics of innovation outputs by industry

Industry	**Description**	**Mean *Patent***	**Mean *CitePat***	**No. of Firm Years**	**% of the Sample**
Chemicals	Chemicals and Allied Products	18.65	3.64	1,485	2.20%
Consumer Durables	Cars, TVs, Furniture, Household Appliances	15.47	5.95	1,880	2.78%
Manufacturing	Machinery, Trucks, Planes, Off Furn., Paper, Commercial Printing	12.07	4.46	7,412	10.98%
Business Equipment	Computers, Software, Electronic Equipment	11.87	6.49	13,013	19.27%
Healthcare	Healthcare, Medical Equipment, Drugs	6.24	4.68	6,914	10.24%
Energy	Oil, Gas, Coal Extraction and Products	2.81	1.31	2,694	3.99%
Telecommunication	Telephone, TV Transmission	3.02	1.26	1,896	2.81%
Consumer Non-Durables	Toys, Food, Tobacco, Textiles, Apparels, Leather	1.68	1.83	3,634	5.38%
Other	Mines, Construction, Building Materials, Transportation, Hotels	0.99	1.24	8,720	12.91%
Wholesale	Wholesale, Retail, Repair Shops, Other Services	0.21	0.45	6,987	10.35%
Finance	Finance, Money	0.13	0.29	10,517	15.57%
Utilities	Utilities	0.08	0.48	2,379	3.52%

This table presents descriptive statistics of innovation outputs by Fama-French 12 industries. The sample is based on the availability of the composite measure. *Patent* is the number of patents. *CitePat* is the number of citations per patent.

TABLE 3 Internal information quality and innovation outputs

Panel A: Accessibility of Internal Information

	Pred. Sign	***Log Patent$_{t+1}$*** **(1)**	***Log Patent$_{t+2}$*** **(2)**	***Log Patent$_{t+3}$*** **(3)**	***Log CitePat$_{t+1}$*** **(4)**	***Log CitePat$_{t+2}$*** **(5)**	***Log CitePat$_{t+3}$*** **(6)**
DRET	+	0.067***	0.078***	0.074***	0.047*	0.060***	0.050**
		(2.66)	(3.04)	(2.95)	(1.87)	(2.62)	(2.38)
LogSIZE	+	0.208***	0.204***	0.193***	0.097***	0.093***	0.087***
		(15.17)	(14.85)	(14.33)	(14.42)	(14.64)	(14.51)
TobinQ	+	0.051***	0.056***	0.053***	0.044***	0.040***	0.025***
		(7.09)	(7.45)	(7.16)	(6.90)	(6.64)	(4.79)
ROA	+	0.117	0.189**	0.236***	0.321***	0.368***	0.392***
		(1.47)	(2.41)	(3.14)	(4.47)	(5.71)	(6.65)
LEV	-	-0.148**	-0.135**	-0.153***	-0.202***	-0.136***	-0.161***
		(-2.49)	(-2.33)	(-2.78)	(-4.52)	(-3.33)	(-4.38)
R&D	+	2.934***	2.653***	2.450***	2.488***	2.138***	1.905***
		(14.76)	(13.42)	(12.72)	(14.58)	(13.47)	(12.97)
CAPEX	+	1.006***	1.203***	1.241***	0.756***	0.877***	0.905***
		(5.59)	(6.42)	(6.68)	(5.17)	(6.31)	(6.91)
PPE	-	-0.184**	-0.196***	-0.184**	-0.188***	-0.166***	-0.142***
		(-2.37)	(-2.58)	(-2.48)	(-3.51)	(-3.39)	(-3.13)
STDEARN	+	0.014	0.021	0.024	0.018*	0.017*	0.014
		(0.93)	(1.34)	(1.46)	(1.81)	(1.79)	(1.54)
LogAGE	+	0.193***	0.170***	0.157***	0.115***	0.099***	0.090***
		(9.54)	(8.48)	(8.15)	(7.70)	(7.11)	(7.02)
HHI	+	0.000	-0.017	0.036	0.206	0.133	0.077
		(0.00)	(-0.09)	(0.20)	(1.51)	(1.05)	(0.64)
HHI^2	+	0.129	0.161	0.125	-0.153	-0.079	0.011
		(0.55)	(0.69)	(0.54)	(-0.99)	(-0.55)	(0.08)
Year/Industry		Yes	Yes	Yes	Yes	Yes	Yes
N		46,061	43,949	41,658	46,061	43,949	41,658
Adjusted R^2		0.321	0.295	0.279	0.261	0.237	0.230

Panel B: Accuracy of Internal Information

	Pred. Sign	***Log Patent$_{t+1}$* (1)**	***Log Patent$_{t+2}$* (2)**	***Log Patent$_{t+3}$* (3)**	***Log CitePat$_{t+1}$* (4)**	***Log CitePat$_{t+2}$* (5)**	***Log CitePat$_{t+3}$* (6)**
MACC	+	0.234**	0.194**	0.163**	0.254***	0.135**	0.092*
		(2.29)	(2.06)	(1.96)	(3.01)	(2.12)	(1.86)
LogSIZE	+	0.280***	0.264***	0.235***	0.108***	0.098***	0.082***
		(14.84)	(14.40)	(13.65)	(13.14)	(13.50)	(13.10)
TobinQ	+	0.064***	0.071***	0.071***	0.039***	0.035***	0.028***
		(4.93)	(5.38)	(5.42)	(4.06)	(4.19)	(3.86)
ROA	+	0.179	0.214*	0.161	0.245**	0.347***	0.266***
		(1.56)	(1.94)	(1.61)	(2.48)	(4.34)	(3.79)
LEV	-	-0.152*	-0.132	-0.152**	-0.182***	-0.136***	-0.143***
		(-1.71)	(-1.55)	(-1.98)	(-3.08)	(-2.64)	(-3.40)
R&D	+	3.895***	3.187***	2.583***	2.784***	2.170***	1.494***
		(12.86)	(11.17)	(9.98)	(12.15)	(11.00)	(8.96)
CAPEX	+	1.393***	1.471***	1.289***	0.769***	0.676***	0.643***
		(4.83)	(5.02)	(4.77)	(3.41)	(3.35)	(3.57)
PPE	-	-0.254**	-0.267***	-0.223**	-0.125*	-0.100*	-0.076*
		(-2.45)	(-2.66)	(-2.39)	(-1.95)	(-1.89)	(-1.65)
STDEARN	+	0.007	0.012	0.015	0.033**	0.026**	0.024**
		(0.30)	(0.53)	(0.70)	(2.18)	(1.96)	(2.09)
LogAGE	+	0.206***	0.185***	0.173***	0.127***	0.105***	0.093***
		(7.13)	(6.70)	(6.86)	(6.89)	(6.56)	(6.79)
HHI	+	0.04	0.035	0.094	0.327*	0.289**	0.158
		(0.15)	(0.14)	(0.40)	(1.90)	(2.02)	(1.31)
HHI^2	+	0.104	0.078	0.04	-0.266	-0.241	-0.094
		(0.32)	(0.25)	(0.14)	(-1.38)	(-1.54)	(-0.69)
Year/Industry		Yes	Yes	Yes	Yes	Yes	Yes
N		20,436	19,400	18,362	20,436	19,400	18,362
Adjusted R^2		0.364	0.336	0.308	0.251	0.232	0.213

Panel C: Timeliness of Internal Information

	Pred. Sign	***Log Patent$_{t+1}$*** **(1)**	***Log Patent$_{t+2}$*** **(2)**	***Log Patent$_{t+3}$*** **(3)**	***Log CitePat$_{t+1}$*** **(4)**	***Log CitePat$_{t+2}$*** **(5)**	***Log CitePat$_{t+3}$*** **(6)**
TIME	+	1.185***	1.064***	0.926***	1.313***	1.096***	0.872***
		(8.29)	(7.48)	(6.68)	(11.02)	(9.93)	(8.31)
LogSIZE	+	0.201***	0.199***	0.190***	0.088***	0.089***	0.086***
		(18.19)	(17.72)	(17.02)	(17.06)	(17.58)	(17.42)
TobinQ	+	0.040***	0.045***	0.043***	0.040***	0.035***	0.023***
		(6.97)	(7.64)	(7.41)	(7.65)	(7.09)	(5.29)
ROA	+	0.050	0.094	0.125**	0.217***	0.233***	0.257***
		(0.82)	(1.56)	(2.12)	(3.91)	(4.56)	(5.34)
LEV	-	-0.122***	-0.124***	-0.143***	-0.137***	-0.108***	-0.138***
		(-2.71)	(-2.78)	(-3.33)	(-3.97)	(-3.39)	(-4.65)
R&D	+	2.657***	2.411***	2.218***	2.222***	1.875***	1.701***
		(17.68)	(16.09)	(15.18)	(16.64)	(14.97)	(14.45)
CAPEX	+	1.104***	1.215***	1.237***	0.824***	0.863***	0.881***
		(8.49)	(9.08)	(9.29)	(7.99)	(8.88)	(9.31)
PPE	-	-0.171***	-0.169***	-0.162***	-0.182***	-0.143***	-0.128***
		(-3.02)	(-2.98)	(-2.92)	(-4.44)	(-3.73)	(-3.47)
STDEARN	+	0.022*	0.025**	0.025*	0.024***	0.020**	0.014*
		(1.78)	(1.96)	(1.92)	(2.99)	(2.40)	(1.77)
LogAGE	+	0.155***	0.138***	0.131***	0.124***	0.108***	0.099***
		(10.33)	(9.24)	(9.13)	(10.86)	(9.97)	(9.64)
HHI	+	0.122	0.080	0.090	0.257**	0.167*	0.112
		(0.86)	(0.56)	(0.66)	(2.40)	(1.66)	(1.16)
HHI^2	+	0.030	0.083	0.094	-0.191	-0.090	-0.019
		(0.17)	(0.46)	(0.54)	(-1.53)	(-0.76)	(-0.16)
Year/Industry		Yes	Yes	Yes	Yes	Yes	Yes
N		87,902	84,501	81,097	87,902	84,501	81,097
Adjusted R^2		0.321	0.297	0.282	0.254	0.233	0.226

Panel D: Composite Measure of Internal Information Quality

	Pred. Sign	***Log Patent***$_{t+1}$ **(1)**	***Log Patent***$_{t+2}$ **(2)**	***Log Patent***$_{t+3}$ **(3)**	***Log CitePat***$_{t+1}$ **(4)**	***Log CitePat***$_{t+2}$ **(5)**	***Log CitePat***$_{t+3}$ **(6)**
COMPOSIT	+	0.390***	0.372***	0.333***	0.355***	0.302***	0.248***
		(10.95)	(10.63)	(10.08)	(12.40)	(11.74)	(10.80)
LogSIZE	+	0.184***	0.177***	0.164***	0.081***	0.075***	0.066***
		(17.81)	(17.31)	(16.63)	(16.95)	(16.92)	(16.61)
TobinQ	+	0.042***	0.049***	0.048***	0.044***	0.039***	0.029***
		(7.29)	(8.14)	(8.19)	(8.52)	(8.17)	(7.08)
ROA	+	0.052	0.083	0.107*	0.218***	0.223***	0.232***
		(0.88)	(1.43)	(1.95)	(4.02)	(4.61)	(5.41)
LEV	-	-0.082*	-0.075	-0.086**	-0.118***	-0.077**	-0.096***
		(-1.73)	(-1.62)	(-1.97)	(-3.38)	(-2.46)	(-3.54)
R&D	+	2.388***	2.078***	1.840***	2.059***	1.620***	1.376***
		(17.12)	(15.33)	(14.46)	(16.47)	(14.51)	(14.03)
CAPEX	+	1.146***	1.249***	1.222***	0.770***	0.756***	0.764***
		(8.18)	(8.72)	(8.83)	(6.84)	(7.31)	(8.02)
PPE	-	-0.219***	-0.217***	-0.204***	-0.207***	-0.161***	-0.141***
		(-3.78)	(-3.80)	(-3.74)	(-5.15)	(-4.53)	(-4.46)
STDEARN	+	0.022*	0.028**	0.028**	0.025***	0.023***	0.016**
		(1.93)	(2.32)	(2.30)	(3.15)	(3.05)	(2.40)
LogAGE	+	0.141***	0.125***	0.116***	0.103***	0.088***	0.076***
		(8.63)	(7.77)	(7.70)	(8.91)	(8.44)	(8.11)
HHI	+	0.032	0.026	0.067	0.221**	0.169*	0.151*
		(0.20)	(0.17)	(0.46)	(1.99)	(1.69)	(1.71)
HHI^2	+	0.153	0.163	0.137	-0.116	-0.067	-0.047
		(0.78)	(0.84)	(0.73)	(-0.90)	(-0.58)	(-0.45)
Year/Industry		Yes	Yes	Yes	Yes	Yes	Yes
N		67,531	64,130	60,726	67,531	64,310	60,726
Adjusted R^2		0.305	0.278	0.259	0.240	0.214	0.203

This table presents the regression results of the relation between internal information quality and innovation outputs. Panels A, B, C, D use *DRET*, *MACC*, *TIME* and *COMPOSIT* as a proxy for IIQ, respectively. *LogPatent* is logarithm of one plus number of patents. *LogCitePat* is logarithm of one plus number of citations per patent. *DRET* is the absolute difference of insider trading returns between top and lower-level managers. *MACC* is management forecast accuracy. *TIME* is timeliness of earnings announcement. *COMPOSIT* is the composite measure of the three internal information quality proxies. Detailed definitions of all variables are provided in Appendix. *t*-statistics presented in parentheses are based on firm-clustered standard errors. ***, **, * indicate significance at the 1%, 5% and 10% two-tailed level, respectively.

TABLE 4 Cross-sectional analysis of internal information quality and innovation outputs

Panel A: Firm Decentralization

		DRET		***MACC***		***TIME***		***COMPOSIT***	
Variable	**Pred. Sign**	***Log Patent$_{t+1}$*** **(1)**	***Log CitePat$_{t+1}$*** **(2)**	***Log Patent$_{t+1}$*** **(3)**	***Log CitePat$_{t+1}$*** **(4)**	***Log Patent$_{t+1}$*** **(5)**	***Log CitePat$_{t+1}$*** **(6)**	***Log Patent$_{t+1}$*** **(7)**	***Log CitePat$_{t+1}$*** **(8)**
IIQ	?	-0.018	0.021	0.061	0.293***	-0.177	0.946***	0.014	0.245***
		(-0.62)	(0.66)	(0.46)	(2.82)	(-1.07)	(6.40)	(0.32)	(6.53)
HDCENTR	?	0.360***	0.134**	0.280***	0.093***	0.491***	0.307***	-0.447***	-0.136***
		(7.97)	(4.25)	(6.07)	(3.02)	(12.43)	(6.38)	(-7.23)	(-3.24)
IIQ × *HDCENTR*	+	0.418***	0.187***	1.034**	0.234	5.356***	1.434***	1.309***	0.451***
		(4.62)	(2.67)	(4.22)	(1.18)	(10.78)	(4.88)	(10.28)	(6.05)
Controls		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year/Industry		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N		36,685	36,685	16,817	16,817	71,246	71,246	52,865	52,865
Adjusted R^2		0.348	0.265	0.382	0.254	0.357	0.260	0.339	0.247

Panel B: Management Team Tenure

Variable	Pred. Sign	*DRET* Log $Patent_{t+1}$ (1)	*DRET* Log $CitePat_{t+1}$ (2)	*MACC* Log $Patent_{t+1}$ (3)	*MACC* Log $CitePat_{t+1}$ (4)	*TIME* Log $Patent_{t+1}$ (5)	*TIME* Log $CitePat_{t+1}$ (6)	*COMPOSIT* Log $Patent_{t+1}$ (7)	*COMPOSIT* Log $CitePat_{t+1}$ (8)
IIQ	?	-0.001	-0.010	0.444	0.305	2.202***	1.261***	0.389***	0.246***
		(-0.02)	(-0.24)	(1.37)	(1.37)	(6.06)	(4.59)	(5.11)	(4.43)
STTENURE	?	0.016	0.032	-0.017	0.007	0.071	0.121***	-0.153***	-0.137***
		(0.67)	(1.62)	(-0.59)	(0.30)	(1.49)	(3.27)	(-2.98)	(-3.01)
IIQ × *STTENURE*	+	0.142**	0.121*	0.047	0.144	0.549*	0.894***	0.258***	0.252***
		(1.97)	(1.84)	(0.15)	(0.49)	(1.79)	(2.88)	(3.19)	(3.64)
Controls		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year/Industry		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N		22,001	22,001	12,107	12,107	28,333	28,333	28,333	28,333
Adjusted R^2		0.400	0.327	0.430	0.319	0.401	0.325	0.402	0.325

Panel C: Length of Product Development Cycle

Variable	Pred. Sign	*DRET* Log $Patent_{t+1}$ (1)	*DRET* Log $CitePat_{t+1}$ (2)	*MACC* Log $Patent_{t+1}$ (3)	*MACC* Log $CitePat_{t+1}$ (4)	*TIME* Log $Patent_{t+1}$ (5)	*TIME* Log $CitePat_{t+1}$ (6)	*COMPOSIT* Log $Patent_{t+1}$ (7)	*COMPOSIT* Log $CitePat_{t+1}$ (8)
IIQ	?	-0.112***	0.003	-0.279**	-0.047	-1.644***	-0.366***	-0.261***	-0.042
		(-3.83)	(0.09)	(-2.49)	(-0.47)	(-9.80)	(-2.57)	(-6.64)	(-1.36)
LPDCYCLE	?	0.618***	0.464***	0.569***	0.405***	1.094***	0.762***	-0.183***	-0.010
		(14.19)	(13.31)	(12.02)	(11.69)	(19.28)	(17.07)	(-4.41)	(-0.31)
IIQ × *LPDCYCLE*	+	0.349***	0.099**	1.037***	0.568***	5.053***	2.952***	1.193***	0.684***
		(6.50)	(2.03)	(5.54)	(3.81)	(16.28)	(12.65)	(14.95)	(12.60)
Controls		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year/Industry		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N		46,061	46,061	20,436	20,436	87,902	87,902	67,531	67,531
Adjusted R^2		0.345	0.279	0.388	0.269	0.351	0.272	0.337	0.259

This table presents the regression results of the relation between internal information quality and innovation outputs conditional on the level of internal information friction. Panels A, B, and C use firm decentralization, management team tenure, and product development cycle as proxies for information frictions. *HDCENTR* is high firm decentralization, an indicator variable that equals one if the annual rankings of business diversification and geographic dispersion are above its respective median, zero otherwise. *STTENURE* is short team tenure, an indicator variable that equals one if the duration of a firm's top management team tenure is in the lowest quintile of the sample, zero otherwise. *LPDCYCLE* is long product development cycle, an indicator variable that equals one if the commercial life of the products emerge from R&D in the industry has an amortization period of five years or longer, and zero otherwise. *LogPatent* is logarithm of one plus number of patents. *LogCitePat* is logarithm of one plus number of citations per patent. *DRET* is the absolute difference of insider trading returns between top and lower-level managers. *MACC* is management forecast accuracy. *TIME* is timeliness of earnings announcement. *COMPOSIT* is the composite measure of the three internal information environment proxies. Control variables are the same as those presented in Table 3. *t*-statistics presented in parentheses are based on firm-clustered standard errors. ***, **, * indicate significance at the 1%, 5% and 10% two-tailed level, respectively.

TABLE 5 Internal control weakness remediation and innovation outputs

Variable	**Pred. Sign**	***LogPatent*$_{t+1}$** **(1)**	***LogCitePat*$_{t+1}$** **(2)**
MW	-	-0.069	-0.011
		(-1.11)	(-0.24)
POST	?	-0.320***	-0.208***
		(-11.46)	(-8.18)
MW × *POST*	+	0.093**	0.114*
		(1.97)	(1.93)
LogSIZE	+	0.217***	0.081***
		(11.96)	(10.05)
TobinQ	+	0.056***	0.042***
		(3.79)	(3.42)
ROA	+	0.023	0.111
		(0.15)	(0.95)
LEV	-	-0.108	-0.131**
		(-1.07)	(-1.97)
R&D	+	3.092***	1.700***
		(9.29)	(7.00)
CAPEX	+	0.675**	0.146
		(2.15)	(0.63)
PPE	-	-0.378***	-0.160**
		(-2.97)	(-2.12)
STDEARN	+	-0.044**	-0.021
		(-2.09)	(-1.57)
LogAGE	+	0.141***	0.045**
		(3.91)	(2.04)
HHI	+	-0.698**	-0.077
		(-2.22)	(-0.40)
HHI^2	+	1.058***	0.279
		(2.60)	(1.23)
Year/Industry		Yes	Yes
N		11,516	11,516
Adjusted R^2		0.322	0.190

This table presents the results of the effect of improvement in internal control quality on innovation outputs. *MW* is an indicator variable that equals one if the firm initially disclosed a Section 404 material weakness in 2004 but remedied it immediately (i.e., the firm did not disclose a Section 404 material weakness after 2004), and zero if the firm did not disclose any material weakness. *POST* is an indicator variable equal to one if the fiscal year is in 2005, 2006 or 2007, and zero if the fiscal year is in 2001, 2002 or 2003. *MW*×*POST* is the interaction of the two variables. *LogPatent* is logarithm of one plus number of patents. *LogCitePat* is logarithm of one plus number of citations per patent. All other variables are defined in Appendix. *t*-statistics are based on firm-clustered standard errors. ***, **, * indicate significance at the 1%, 5% and 10% two-tailed level, respectively.

TABLE 6 Internal information quality and innovation outputs – additional controls

	Pred. Sign	***Log Patent$_{t+1}$* (1)**	***Log CitePat$_{t+1}$* (2)**	***Log Patent$_{t+1}$* (3)**	***Log CitePat$_{t+1}$* (4)**
COMPOSIT	+	0.495***	0.532***	0.488***	0.455***
		(7.86)	(10.30)	(3.49)	(4.28)
AQ	+	0.168**	0.292***	0.080	0.267*
		(2.52)	(4.48)	(0.44)	(1.66)
INST_TRAN	-			-0.761***	0.062
				(-3.76)	(0.38)
INST_DEDI	+			0.198	0.116
				(0.55)	(0.44)
NUMA	-			0.042***	0.018***
				(6.68)	(4.57)
LIQ	-			-0.091**	-0.053**
				(-2.15)	(-2.03)
TAKEOVER	+/-			2.785*	0.769
				(1.93)	(0.63)
EXEC_OWN	-			-0.001**	-0.001***
				(-2.49)	(-3.58)
EXEC_COMP	+/-			0.015	-0.009
				(0.77)	(-0.75)
RET	+			0.064***	0.045*
				(2.62)	(1.96)
STDRET	+			1.343***	1.054***
				(3.95)	(3.89)
STDCFO	+			0.001***	0.000***
				(5.59)	(3.45)
AFDISP	+/-			0.008	-0.005
				(0.30)	(-0.24)
Other Controls		Yes	Yes	Yes	Yes
Year/Industry		Yes	Yes	Yes	Yes
N		30,899	30,899	10,043	10,043
Adjusted R^2		0.329	0.233	0.478	0.364

This table presents the results of the relation between internal information quality and innovation outputs controlling for accruals quality, corporate governance, and managerial career risk and ability. *AQ* is accruals quality. *INST_TRAN* is transient institutional ownership. *INST_DEDI* is dedicated institutional ownership. *NUMA* is number of analysts. *LIQ* is stock liquidity. *TAKEOVER* is takeover pressure. *EXEC_OWN* is executive ownership. *EXEC_COMP* is executive compensation. *RET* is stock return. *STDRET* is return volatility. *STDCFO* is cash flow volatility. *AFDISP* is analyst forecast dispersion. Other control variables are the same as those presented in Table 3. Detailed definitions of all variables are provided in Appendix. t-statistics in parentheses are based on firm-clustered standard errors. ***, **, * indicate significance at the 1%, 5% and 10% two-tailed level, respectively.

TABLE 7 Alternative model specifications

Panel A: Tobit Regressions

	Pred. Sign	***Log Patent***$_{t+1}$ **(1)**	***Log Patent***$_{t+2}$ **(2)**	***Log Patent***$_{t+3}$ **(3)**	***Log CitePat***$_{t+1}$ **(4)**	***Log CitePat***$_{t+2}$ **(5)**	***Log CitePat***$_{t+3}$ **(6)**
COMPOSIT	+	1.421***	1.811***	1.877***	1.794***	2.053***	1.961***
		(11.13)	(11.04)	(10.92)	(11.90)	(11.72)	(10.74)
Controls		Yes	Yes	Yes	Yes	Yes	Yes
Industry/Year		Yes	Yes	Yes	Yes	Yes	Yes
N		67,531	64,130	60,726	67,531	64,130	60,726
Pseudo R^2		0.224	0.230	0.233	0.195	0.215	0.232

Panel B: Negative Binomial Regressions

	Pred. Sign	***Patent***$_{t+1}$ **(1)**	***Patent***$_{t+2}$ **(2)**	***Patent***$_{t+3}$ **(3)**	***CitePat***$_{t+1}$ **(4)**	***CitePat***$_{t+2}$ **(5)**	***CitePat***$_{t+3}$ **(6)**
COMPOSIT	+	1.153***	1.285***	1.352***	0.737***	1.009***	0.917***
		(7.21)	(6.93)	(7.46)	(4.14)	(4.98)	(4.08)
Controls		Yes	Yes	Yes	Yes	Yes	Yes
Industry/Year		Yes	Yes	Yes	Yes	Yes	Yes
N		67,531	64,130	60,726	67,531	64,130	60,726
Pseudo R^2		0.145	0.140	0.146	0.060	0.083	0.104

This table presents the results of the relation between internal information quality and innovation outputs using alternative model specifications. In Panel A *LogPatent* is logarithm of one plus number of patents. *LogCitePat* is logarithm of one plus number of citations per patent. In Panel B, Patent is the number of patents; *CitePat* is the number of citations per patent. Both *Patent* and *CitePat* are rounded to the nearest integers. Control variables are the same as those presented in Table 3. t-statistics and z-statistics in parentheses are based on firm-clustered standard errors. ***, **, * indicate significance at the 1%, 5% and 10% two-tailed level, respectively.