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Highlights

- Transparency promotes a firm's innovative *effort* and *efficiency*.
- Transparency directly boosts managers' innovative *effort*, through its implicit contracting role, by reducing managerial career concerns, rather than indirectly, through improved access to external financing.
- Transparency enhances innovative *efficiency* through its governance role in facilitating more efficient allocation of R&D capital.
- The benefit of transparency for innovation is attenuated in environments with higher proprietary cost

• Transparency and Firm Innovation

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Abstract

Firm innovation drives both firm competitiveness and economic growth. Constructing a novel firm-patent panel database from 29 countries, I find that transparency directly boosts innovative effort by reducing managerial career concerns. This effect operates through transparency's implicit contracting role: it reduces the sensitivity of management turnover to poor innovative output. Transparency also increases innovative efficiency through its governance role in facilitating efficient allocation of R&D capital. Nonetheless, the benefit of transparency is fully offset in environments with greater proprietary cost. These findings illuminate the unique roles and mechanisms of transparency in promoting innovation incentives and outcomes.

Keywords: R&D; career concern; management turnover; implicit contracting; proprietary cost; corporate governance

JEL classification: G15; G30; M40; M41; N20

1. Introduction

Understanding the economic consequences of a firm's information environment (firm transparency) is an important theme in accounting research.[1] One line of the inquiry points to financial reporting quality as a means of improving the efficiency of fixed capital investment (Biddle et al., 2009; Verdi, 2006). However, the literature provides little evidence regarding the link between transparency and firm innovation. This is a notable gap, given that innovation, unlike fixed capital investment, is a long-term intangible investment with high uncertainty and secrecy (Hall, 2002), but acts as a key driver of the real economy (Solow, 1957). My study aims to address this gap by examining the effects of firm transparency on innovative effort and efficiency and unraveling the mechanisms underlying these effects.

Unlike fixed capital, which is prone to overinvestment, research and development (R&D) is typically underinvested, due to internal managerial incentives (Holmstrom, 1989) as well as external financial constraints (Brown et al., 2013; Hall, 2002). While studies suggest that better quality information can mitigate underinvestment of fixed capital by improving firms' access to lower-cost external capital (e.g., Biddle et al., 2009), it is not clear whether financing *alone* will spur managerial innovative effort. In a multi-task setting, risk-averse managers have a natural incentive to forgo intangible R&D investments because they carry more risk than fixed capital investments (Kothari et al., 2002) and managers bear full career consequences if innovation fails for purely stochastic reasons (Hirshleifer, 1993; Kaplan and Minton, 2012). If explicit contracts cannot fully overcome the incentive problem, transparency can shield managers from undue career risks by providing principals detailed firm-specific information on managerial actions and helping them filter out noise from uncontrollable market risks (Bushman and Smith, 2001). In a multiperiod contracting relationship, managers in more transparent firms are thus encouraged to exert greater innovative effort.[2] This implicit contracting role of transparency predicts a positive relation between firm transparency and innovative effort (i.e., R&D investment).

[1] Transparency is defined as the availability of *firm-specific* information that reveals underlying economic activities to outsiders (Bushman et al., 2004b).
[2] As discussed in review papers by Bushman and Smith (2001) and Lang and Maffett (2011), the role of transparency in affecting economic performance through managerial incentives is likely to be a first-order effect.

Greater innovative effort, however, does not necessarily translate into higher innovative efficiency, i.e., innovative output (patents/citations) for a given level of input (R&D investment) (Hirshleifer et al., 2013). Although innovative efficiency matters vitally for firm competitiveness, managers face significant challenges in selecting and prioritizing valuable R&D projects (Costello, 1983). During implementation, self-serving managers may also extract private benefits from R&D capital through risk substitution (Billings et al., 2014), insider trading (Aboody and Lev, 2000), or myopic R&D manipulation (Graham et al., 2005). Transparency, by providing verifiable financial information on firm value and managerial actions, can help managers better calibrate returns on prospective projects, discipline them during implementation, and ensure that R&D capital is directed to its best uses. This governance role points to a positive relation between transparency and innovative efficiency.

The latter prediction, however, may not be borne out empirically because transparency may also reveal proprietary strategic information to competitors, reducing the value of a potential innovation (Bhattacharya and Ritter, 1983). Financial information is frequently exploited by peer firms, including competitors (Pae, 2002; Simons, 1990). These information leakages can result in a loss of competitive edge, and greater transparency may thus undercut innovative efficiency. In light of this double-edged effect of transparency, its net effect on innovative efficiency is an empirical question.

To test my predictions, I employ a fixed-effect panel-based identification approach to analyze a large firm-level panel dataset consisting of 88,687 firm-year observations from 12,930 publicly traded firms from 29 countries during the period of 1990 through 2010. I construct this dataset by matching financial data from Worldscope with patent data from the U.S. Patent and Trademark Office (USPTO) at the firm level. This novel international *micro*-level firm-patent matched dataset enables me to move beyond aggregated country-level analysis to examine the impact of a firm's information environment on its innovative incentive and outcomes; the dataset's three-dimensional (country-firm-year) nature also allows me to control for a wide array of omitted variables.

My empirical analyses yield two major findings. First, I provide strong evidence that firm transparency significantly increases managerial effort in R&D investment, even after controlling for access to external financing. This result holds for all six firm-level transparency measures, including three measures of financial reporting quality (Leuz et al., 2003), one measure of the use of international accounting standards (Daske et al., 2013), and two measures of the quality of the external information environment—analyst following and analyst forecast accuracy (Lang et al., 2012; Lang and Lundholm, 1996). Further analysis reveals that transparency boosts R&D effort through its implicit contracting role by reducing the sensitivity of management turnover to (poor) innovative output. Cross-sectional results confirm that the incremental effect of transparency on R&D investment is more pronounced when managers face greater ex-ante career risks of investing in R&D, for example, when they work in firms with lower insider ownership or longer product development cycles.

Second, I find that transparency significantly improves innovative efficiency. This efficiency gain stems primarily from the governance role of transparency in facilitating better allocation of R&D capital to investment opportunities. Cross-sectional analysis provides consistent evidence that the positive effect of transparency is significantly stronger for firms subject to greater monitoring demand (i.e., those with greater organizational complexity or in countries with weaker governance regimes), where the risk of resource misallocation is higher and hence the governance role of transparency more valuable. However, this benefit is damped by proprietary cost, for example, in countries with relatively weak intellectual property rights.

To alleviate endogeneity concerns, I employ a wide range of empirical strategies. To limit the concern of omitted country-level variables, I include country-fixed effects in all regressions. In addition, I conduct a separate single-country analysis using only the U.S. firms. The identification thus only exploits within country cross-sectional variation in firm transparency and innovation, holding national institutional details constant. To address reverse causality, I employ a difference-in-differences approach using the mandatory adoption of International Financial Reporting Standards (IFRS) as an exogenous shock to transparency and find that mandatory adopters experienced a relatively larger increase in innovation, compared to non-adopters. I next analyze the details of dynamic changes of transparency on innovation and find that only *lag* changes in transparency are associated with *future* changes in innovation but *lead* changes in transparency are not associated with *past* changes in innovation. I further demonstrate that my estimates are robust to controlling for potential cross-sectional correlation using within-country or within-year regressions as well as a robust standard error estimation method that treats countries as clusters. Finally, I include *country*year* and *firm-fixed* effects in the models to fully absorb country-level macroeconomic shocks and cross-firm heterogeneity. My results are also robust to controlling for managerial foresight of financing needs and growth opportunities, R&D reporting biases, institutional ownership, potential sample bias, and the use of an alternative patent database. The robustness and consistency across all these analyses suggest that my results are unlikely driven by omitted variables, reverse causality, or simultaneity.

My study contributes to the literature in several ways. First, it extends the research on accounting information and real investment decisions (e.g., Biddle et al., 2009; Francis et al., 2009; Verdi, 2006). Research in this area has focused on fixed capital investment and argued that information quality reduces underinvestment by improving firms' access to external financing. My study differs in that it focuses on innovation, an intangible, high-risk, and proprietary investment of fundamental importance to economy. My results show that transparency directly increases managers' *incentive* to invest in R&D by reducing their career concerns. Moreover, unlike studies examining only the level of investment, my results demonstrate that transparency promotes the *efficiency* of innovation in converting R&D investment into patents and citations. My findings also underscore the potential proprietary cost arising from transparency when intellectual property rights are weak.

Second, my study contributes to the broad literature examining accounting systems and economic performance (e.g., Brown and Martinsson, 2014; Rajan and Zingales, 1998). Country-level studies have generally relied on aggregated accounting indices and pointed to the reduction of financing cost as the combined effect of the accounting system in promoting economic growth. By implementing a *micro*-level analysis at the firm-level, my study disentangles the *governance* role of transparency from its general effect on external financing and uncovers the mechanism: specifically, it demonstrates that transparency increases the responsiveness of R&D investment to the investment opportunity set, leading to higher innovative efficiency. To this end, it also helps address the call of Bushman and Smith (2001) for more research on the first-order effect of accounting information on economic performance.

Lastly, this study adds to the research on implicit contracting role of accounting information (Bushman et al., 2004a; Hope and Thomas, 2008). Given the inherent incompleteness of explicit contracts, implicit arrangements between firms and managers govern a substantial portion of their contracting relationship. While the implicit contracting role of accounting information is theoretically appealing, Armstrong et al. (2010, p.204) note that "we are aware of little research examining how or whether accounting information is used in informal (implicit) multiperiod contracting with executives, but we believe that this direction may prove fruitful in reviving research in this area." By showing that transparency significantly reduces the sensitivity of management dismissal to innovation failures, my study provides new evidence on the implicit contracting role of transparency in enabling principals to better assess managers' innovation performance and thus shield them from undue career risks.

The remainder of this paper proceeds as follows. Section 2 develops the hypotheses. Section 3 describes sample construction, data sources, and variables. Section 4 outlines the empirical models and reports main empirical results. Section 5 discusses identification strategies. Section 6 presents additional analyses and sensitivity tests. Finally, section 7 concludes.

2. Related Literature and Hypothesis Development

This study builds on the governance research in accounting investigating the properties of accounting information in support of effective governance and economic performance (Bushman and Smith, 2001). One stream of literature suggests high quality accounting information can improve investment efficiency by mitigating the information asymmetry between corporate managers and capital suppliers (see Healy and Palepu (2001) for a review). In doing so, high quality reporting allows financially constrained firms to better attract capital from investors and mitigates underinvestment problems; improved accounting quality may also curb managerial incentive to overinvest (and destroy value) through enhanced monitoring or better contracting (Biddle et al., 2009; Francis et al., 2009; Verdi, 2006). In a *credit* market setting, García Lara et al. (2016) find that accounting conservatism mitigates underinvestment, as it facilitates firms' access to debt financing. Bushman et al. (2011) also report that more timely accounting recognition of economic losses disciplines managers to avoid negative net present value investments in fixed assets, thus reducing overinvestment. Jung et al. (2014) extend this line of research to *labor* investment and document that high-quality financial reporting reduces underhiring by reducing adverse selection cost during securities offerings and mitigates overhiring by enhancing outside monitoring. While these studies vary in their settings and empirical measures, the theme is that high-quality accounting helps optimize firms' investments by reducing underinvestment (overinvestment) when firms are financially constrained (unconstrained) through external financing (external monitoring).

These findings, however, may not generalize to innovation. Innovation involves multiple stages, which typically start with intangible investment, such as R&D, and end with commercialization of new products or services protected by patents (Lev, 2001). From the *input* perspective, R&D is a long-term, high-risk investment not only hindered by an external financial constraint but also by internal managerial incentives (Hall, 2002). It is not clear whether lower-cost external financing alone can overcome this internal incentive problem. From the *output* perspective, the creation of a knowledge-based product is proprietary, which makes transparency unlikely to fully solve the agency conflicts because the release of sensitive information can impair the value of an innovation (Bhattacharya and Ritter, 1983; Jaffe, 1996). As a result, how transparency affects innovation remains an open question. The multi-stage nature of innovation provides a natural setting to disentangle differential roles of transparency in influencing a firm's innovative incentives as well as outcomes.

2.1. Transparency and innovative effort

Unlike fixed capital investment, which is prone to overinvestment such as empire building (Hope and Thomas, 2008; Stein, 2003), R&D investment suffers more from underinvestment problems, which originate from both an external financial constraint (Brown et al., 2013; Hall, 2002) and internal managerial incentives (Baysinger et al., 1991; Ferreira et al., 2014; Holmstrom, 1989, 1999). Given the intangible and high-risk nature of R&D, studies suggest that innovating firms rely on costly equity capital as their primary source of financing (Brown et al., 2013; Hall, 2002). By reducing information frictions, transparency can theoretically lower firms' cost of capital (Baiman and Verrecchia, 1996; Diamond and Verrecchia, 1991) and improve their access to external financing, which they need to fuel their innovation.

However, external financing *alone* may not spur innovative effort. Theories suggest that, even without financial constraints, risk-averse managers are rationally biased against innovative projects, which typically entail long investment horizons and high failure rates (Baysinger et al., 1991; Ferreira et al., 2014; Holmstrom, 1989, 1999). In a standard agency framework, since the principals cannot directly observe and contract upon all of the agent's actions, they must rely on ex post observable signals, such as the *output* of the project, to infer managerial ability. Output-based measures, however, are often very noisy and highly aggregated, and thus they cannot say much about specific managerial *actions* taken to achieve the performance (Armstrong et al., 2010). As a result, managers are reluctant to invest in risky, long-term R&D projects because they bear full career consequences if the investment fails for stochastic reasons (Kaplan and Minton, 2012; Zwiebel, 1995).

Explicit contracts, in this context, are unlikely to fully overcome this incentive problem because they are inherently incomplete and cannot fully capture the true marginal product of managerial innovative effort. For instance, earnings-based contracts are unlikely to promote innovation since R&D investment has a multiperiod effect not fully captured by current earnings. While research suggests that stock price can better capture long-term value creation, its forward-looking nature can also limit its usefulness in gauging managers' current contribution (Bushman and Smith, 2003). In fact, standard pay-for-performance schemes with low tolerance for early failure may even exacerbate managerial myopia and impede innovation (Manso, 2011). Furthermore, the explicit contracts for top managers of public firms are typically very short and thus unlikely to shield managers from the career risks of failed innovation (Aghion et al., 2013).

Hence most managers' payoff is not explicitly determined by contracts but *implicitly* by the principals' perception on their ability to recontract.[3] One potential remedy, as noted by Holmstrom (1989, 1999), is close monitoring of managerial *actions* and the use of this information to overcome the limitations of explicit contracting. While full observation of managerial actions is either impossible or prohibitively costly, high-quality accounting information can provide principals additional *detailed* information on managerial actions and thus allow better identification of managerial effort (Armstrong et al., 2010). For example, detailed firm-specific financial information, such as margin analysis, expense ratios, and product-line segment data, can help principals assess the quality of managers in terms of their risk tolerance, strategic vision, investment style, and effort, leading to a better understanding of the relation between the manager's actions and innovative outcomes.

Transparent information also can help principals filter out market noise in output-based measures, avoiding the imposition of unnecessary penalties on managers (Busman and Smith 2001). This *implicit contracting* role of accounting echoes the "informativeness principle" of Holmstrom (1979, p.75), who contends that "… any additional information about the agent action, however imperfect, can be used to improve the welfare of both the principal and the agent." While innovative output can only capture ultimate outcomes, a transparent information environment allows principals to better observe the *path* of managers in achieving this performance. In a multiperiod contracting relationship, managers in more transparent firms are thus encouraged to innovate more in anticipation of lower career risks.[4] Therefore, in my first hypothesis (stated in the alternate form), I expect that higher transparency is associated with greater innovative effort.

H1a: Firm transparency is positively associated with the level of R&D investment, after controlling for access to external financing.

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[3] Implicit contracting represents the equilibrium behavior in a multiperiod repeated game (Armstrong et al., 2010). "Implicit" here refers to the conditions under which principals can monitor the manager while he or she pursues innovative strategies and assess his or her abilities, independent of the outcome of innovation.

[4] Gary Shapiro, the CEO of the Consumer Electronics Association and the author of two best-selling books about innovation, similarly observed: "Innovation is never a safe bet. ... Mistakes are *only* punished if they are *hidden*. Processes and assumptions are re-examined after each failure. New ideas are encouraged (*Forbes*, 2011)." Shapiro's remark highlights the importance of transparency in shielding managers from undue career risks, and encouraging innovative efforts.

An objective of this study is to identify the *mechanism* underlying the documented effect. If transparency improves managers' innovative effort by mitigating their career risks, it should lower the *sensitivity* of management turnover to (poor) innovative output. This leads to my next hypothesis.

> **H1b**: Firm transparency reduces the *sensitivity* of management turnover to innovative output, after controlling for standard performance measures (e.g., earnings and stock performance) and R&D investment.

The relation between transparency and innovative effort is likely to vary cross-sectionally, depending on the level of career risk facing managers. Research suggests that ownership structure is one of key determinants of managerial innovation incentive (Baysinger et al., 1991; Francis and Smith, 1995). Francis and Smith (1995) find that, due to high contracting costs, diffusely held firms are less innovative than those with a high concentration of insider ownership. Holding a lower stake in firms also weakens managers' bargaining power and makes them easier to replace (Shleifer and Vishny, 1989). Therefore, in diffusely held firms where managers have less ownership, these managers may face higher career risks from investing in R&D. A long product development cycle may also increase managers' career risk because managers typically have limited horizons, but returns on R&D investment are not realized until later periods (Zwiebel, 1995). In summary, if transparency increases innovative effort by reducing managerial career concerns, I expect this effect to be more pronounced for firms with lower insider ownership or longer product development cycles.

> **H1c**: The positive association between firm transparency and R&D investment is more pronounced when managers are exposed to higher ex-ante career risks (i.e., when their firms have lower insider ownership or longer product development cycles), ceteris paribus.

2.2. Transparency and Innovative Efficiency

Given limited resources, enhancing firm value is achieved by attaining a high level of efficiency in generating innovative *output* from a given level of R&D *input* (Hirshleifer et al., 2013). While project selection of R&D is the key first step to achieve high innovative efficiency, it is often clouded by its complicated nature, multiperiod resource commitment, and highly uncertain outcome. The success of R&D project selection, therefore, depends critically on how much relevant *information* can be quantified and incorporated into decisions (Meade and Presley, 2002). High quality external information can directly aid managers in internal decision-making in a sense that it conveys the prospect of future growth and helps managers estimate the return of investment opportunities (Beyer et al., 2010; Hemmer and Labro, 2008). Misreported information, in contrast, can generate unrealistic expectations about future growth and distort firms' real decisions (McNichols and Stubben, 2008). An important implication here is that transparency, by reflecting firm value and managerial actions, can serve as a *direct* determinant of R&D project selection.

Transparency can also *indirectly* guide managers in identifying R&D investment opportunities through a learning channel by supporting the informational role of stock price. As illustrated in theoretical work by Dow and Gorton (1997), stock price aggregates information from many different market participants who cannot directly communicate with the firm, and thus it may contain private strategic information that managers otherwise do not have. A growing literature in financial economics finds that managers can learn from the private information in stock price about the prospects of their own firms and thus improve their investment decisions (Chen et al., 2007; Durnev et al., 2004). A transparent information environment can enhance the efficiency of stock price in communicating this sort of information and thus improve managers' ability to learn about investment opportunities (Loureiro and Taboada, 2015). This effect can be particularly important to innovation, because the feedback information in stock price mostly reflects the market demand for the firm's potential products or competition from other firms (Chen et al., 2007).

Better project identification, however, may not alone ensure efficient resource allocation. Greenspan (2002) notes that intangible investments are more susceptible to corporate malfeasance than tangible investments. Self-serving managers with many stock options may focus on high-risk R&D projects to gain short-term profits (Billings et al., 2014). They may also exploit the high information asymmetry associated with R&D and extract private gains from insider trading (Aboody and Lev, 2000) or opportunistically cut R&D expense to meet short-term earnings targets to safeguard their bonus or jobs (Graham et al., 2005). Given the intangible nature of R&D, it is often very difficult for outside investors to detect and scrutinize managerial misbehavior. The idiosyncrasy of R&D further constrains investor ability to derive information on the efficiency or value of a firm's own R&D projects from observing innovative performance of other firms (Aboody and Lev, 2000).

Transparency, by providing *firm-specific* financial information, supports both external and internal governance in disciplining managers and ensuring R&D capital is used prudently.[5] For instance, high quality information, by facilitating direct monitoring, can curb managerial misallocation of R&D capital or opportunistic cuts to R&D expense (Healy and Palepu, 2001). It can also increase the informational efficiency of stock prices used for evaluating and compensating managers (see Bond et al. (2012) for a survey). Moreover, information intermediaries, such as financial analysts, can scrutinize public disclosures, which facilitates the compounding of R&D information into stock price (Kimbrough, 2007), thereby discouraging managers from trading on their private information. Finally, transparency can facilitate corporate takeovers that replace underperforming managers—the mere threat of which can encourage managers to maximize firm value (e.g., Scharfstein, 1988).

In short, transparency can help managers select valuable R&D projects and discipline them during implementation. Resources are thus directed to "projects identified as good and away from projects that primarily benefit managers rather than owners of capital and to prevent stealing" (Bushman and Smith, 2003, p.2). To the extent transparency does this, I expect greater transparency to be associated with more productive innovation.

H2a: Firm transparency is positively associated with innovative *output* and innovative *efficiency*, after controlling for R&D investment.

I next analyze the *source* of such efficiency gains by examining the responsiveness of R&D to investment opportunities. If efficiency gains stem primarily from transparency facilitating the optimal allocation of R&D capital, capital should flow toward good investment opportunities and away from poor

[5] A series of recent innovation scandals (e.g., Valeant, Theranos, Pfizer, etc.) have been attributed to lack of transparency because it significantly restricts outside investors' ability to monitor firms' innovation processes and take early corrective actions. Valeant's shareholders, for instance, were "unpleased by the lack of disclosure" (*Fortune*, 2015). Walgreens, one of Theranos's big shareholders, also questioned the adequacy and quality of financial information provided by Theranos to allow due diligence and effective oversight (*Harvard Law*, 2016).

ones and hence increased *responsiveness* of R&D investment to the investment opportunity set. This leads my next hypothesis.

H2b: Firm transparency increases the *sensitivity* of R&D investment to the investment opportunity set, ceteris paribus.

I further develop two cross-sectional predictions for the transparency-innovative efficiency relation, conditional on monitoring demand and proprietary cost. Research suggests that monitoring demand is greater for firms with multiple industrial/geographical segments because they have more complex managerial decisions and greater difficulty integrating information across their operating units (e.g., Bushman et al., 2004a; Engel et al., 2010). In addition, the extent of monitoring demand is shaped by the strength of the country-level governance regime. When it is weak, managers are less likely to abide by the rules of society; therefore innovation investments are more susceptible to managerial opportunism. In my next hypothesis, I expect that the positive effect of firm transparency on innovative efficiency to be stronger for firms subject to greater monitoring demand, where the risk of resource misallocation is greater and hence so is the *governance* benefit of transparency.

H2c: The positive association between firm transparency and innovative efficiency is more pronounced for firms subject to greater *monitoring demand* (i.e., firms in countries with weaker governance regimes or those with greater organizational complexity), ceteris paribus.

Benefits notwithstanding, transparency may reveal proprietary information to competitors. Bhattacharya and Ritter (1983) model firms' information disclosures and suggest that revealing proprietary information can impair the potential value of an innovation. While a firm's accounting information may not directly reveal technological details, it does serve as a way for peer firms to gain sensitive strategic information (Pae, 2002; Simons, 1990). These information leakages can enable peers to better observe the firm's innovative performance, alter their own R&D policies accordingly or even mimic R&D strategies (Li, 2015). To illuminate the proprietary cost of transparency, I exploit the cross-sectional variation in country-level intellectual property rights protection, which is crucial for protecting the returns of innovation investment against the risk of expropriation (Claessens and Laeven, 2003). Without well-established intellectual property rights, greater transparency can inhibit a firm's ability to generate patents from its R&D investments. Accordingly, I expect that the positive effect of transparency on innovative efficiency is damped in countries with weak systems of intellectual property rights protection, where the proprietary cost of transparency is higher.

H2d: The positive association between firm transparency and innovative efficiency is attenuated in environments with greater *proprietary cost* (i.e., countries with weaker intellectual property rights), ceteris paribus.

3. Sample, Data, and Descriptive Statistics

3.1. Sample and Data Sources

The data in this study is from two major sources: (1) firm-level financial data from the Worldscope database and (2) granted patent data from the U.S. Patent and Trademark Office (USPTO) through the Harvard Patent Network Dataverse (HPND) database, developed by Lai et al. (2011). USPTO patent data has been widely adopted to measure cross-country innovation (e.g., Acharya et al., 2013; Hsu et al., 2014). USPTO patent data should not severely underestimate the innovation of foreign companies because the U.S. has been the largest technology consumption market in the world and large public companies commonly protect their innovations by simultaneously applying for patents at USPTO, the European Patent Office (EPO) , and the Japanese Patent Office (JPO) (Hsu et al., 2014). Moreover, USPTO arguably captures more important inventions because its foreign filers are willing to accept additional costs of patenting abroad.

The initial sample starts with all firm-year observations for publicly listed companies from the Worldscope database from 1990 through 2010 (the ending year with patent data). I restrict my sample to firms with positive R&D expenditures so that my analyses are based upon firms for which innovation is an important component of the business.[6] I also require the countries in my sample to have sufficient financial data for calculating transparency measures and nonmissing data on basic country-level institutional variables (Brown et al., 2013; Claessens and Laeven, 2003; La Porta et al., 1998). I further exclude financial (SIC codes 6000–6999) and utilities firms (SIC codes 4900–4999), because they tend to

[6] For these sample firms, if R&D is missing in some years, I follow prior research (e.g., Bena et al., 2016; He and Tian, 2013) and assume zero values in the regression. My results are robust to deleting missing R&D values.

be regulated. Lastly, I exclude U.S. firms (>50% of the total observations) from my sample to avoid a potentially large sample and local bias (Hsu et al., 2014). Nevertheless, my results are robust to a separate analysis using only the U.S. sample (in section 5.1). To create an annual proxy for innovation for each firm, I match Worldscope firms to firm-level assignees from USPTO to merge the financial data with the patent data on the firm level. The details of algorithm for firm-patent matching are described in Appendix B. My final sample consists of 88,687 firm-year observations from 12,930 public firms from 29 countries from 1990–2010. The sample size for my empirical models may be smaller, due to additional data limitations. To minimize the effect of outliers, I winsorize all continuous variables at the top and bottom 1% of each variable's distribution.

Table 1, panel A, reports the frequency of observations for each country. My overall sample ensures I have a large cross-section of firms over a long time horizon. An advantage of this unique firm-patent matched panel dataset is that it spans 20 years, which allows me to conduct a within-firm analysis exploiting its time-series variation. The wide range of institutional settings also allows me to explore how the effects of firm transparency on innovation vary cross-sectionally with institutional arrangements.

[Insert Table 1]

3.2. Variable Measurement

Innovation Variables

My innovation measures aim to capture both innovative effort and outcome. Following the literature (Bena et al., 2016; Brown et al., 2013; Chang et al., 2013; Hsu et al., 2014), I measure innovative effort using R&D intensity (*R&D*), calculated as R&D investment scaled by total assets. I also construct two patent-based measures to capture innovative output, that is, number of patents (*PATENT*) and number of forward citations (*CITATION*) (Acharya et al., 2013; Hsu et al., 2014). *PATENT* is computed based on each patent's application year, instead of its grant year, because the application year better captures the actual effective time of the innovation (Griliches et al., 1988). *CITATION* is calculated as the total number of citations received by the patents applied for during a given year. This forward-looking measure aims to capture the economic significance of each patent; it reflects the breadth of the patent's influence, its technological quality, and market value (Griliches et al., 1988).

Transparency Variables

To capture the multifaceted nature of transparency, I focus on three key aspects: financial reporting quality, the use of global accounting standards, and the quality of the external information environment. Empirically, I construct the following six *firm*-level measures: (1) earnings smoothing using accruals (*SMOOTH_RATIO*) (Leuz et al., 2003), (2) earnings smoothing based on the correlation between changes in accruals and operating cash flow (*SMOOTH_CORR*) (Barth et al., 2008; Lang et al., 2012), (3) the magnitude of total accruals (*ABS_ACCR*) (Barth et al., 2008; Hope and Thomas, 2008; Leuz et al., 2003), (4) International Accounting Standards (*INT_GAAP*) (Barth et al., 2008; Daske et al., 2013), (5) the number of analysts following (*ANALYST*), and (6) analyst forecast accuracy (*ACCURACY*) (Lang et al., 2012; Lang and Lundholm, 1996).[7] To mitigate potential measurement error, I also create a composite firm-level transparency (*TRANS*) based on the average of the scaled percentile rank of the above six transparency components, with higher values indicating greater transparency.[8] Detailed variable definitions are in Appendix A.

Control Variables

Following the literature (e.g., Aghion et al., 2013; Bena et al., 2016) , I include an extensive array of firm- and country-level controls identified as potential determinants of innovation. First, to disentangle the direct effect of transparency on innovation from its indirect effect through external financing, I control for firms' access to external financing (*FINANCE*), calculated in the spirit of Brown et al. (2013) as the sum of net equity issuance over a five-year rolling window ending with the current year, assuming that all

[7] I do not include voluntary corporate disclosure because of the difficulty in measuring both the level and quality of disclosure policies; see a discussion by Healy and Palepu (2001).

[8] Like Lang et al. (2012), if analyst forecast accuracy (*ACCURACY*) is not available, I use *TRANS* to capture the average percentile rank of the remaining five measures. Results are similar using a factor-weighting analysis. In addition, I split the measures between analyst-related and other variables to distinguish transparency arising from external information gathering from that arising from firm choice. Results are consistent across both groups.

equity financing raised during the past five years contributes to current R&D investment.[9] In addition, I control for total sales (*SALES*), the number of employees (*EMPLOYMENT*), firm age (*FIRM_AGE*), and the ratio of capital to labor (*K/L*). I also include market-to-book ratio (*MTB*), return on assets (*ROA*), and sales growth (*SALES_GROWTH*) to capture growth opportunity and profitability; leverage ratio (*LEV*) and internally generated cash (*CASH*) to account for the effect of capital structure; the Herfindahl index (*HERFINDAHL*) and its square term ($HERFINDAHL^2$) to control for product market competition (Aghion et al., 2005); the percentage of closely held shares (*CLOSE%*) as a proxy for ownership structure; and lastly the percentage of foreign sales (*FOREIGN_SALE%*) and cross-listing status (*ADR*) to control for global market expansion, which may be correlated with both transparency and firm incentive to patent in the United States.

In addition to *country* fixed effects, I also control for several *time-varying* country-level variables to account for differences in macroeconomic factors that might affect firm innovation. Specifically, I include total value of stock traded (*MKT_SIZE*) to control for the breadth of a country's financial market and gross domestic product (*GDP*) and the GDP per capita (*PERCAPITA*) to account for their general effect on economic well-being of the country and the overall quality of legal environment (La Porta et al., 1998).

3.3. Descriptive Statistics and Correlations

Table 1, panel B, reports descriptive statistics and univariate analysis at the firm-level. The statistics on innovation show that the number of patents and number of citations is highly skewed. To mitigate this, I follow prior studies and log transform these variables in the regression analyses.[10] I next report the distribution of innovation across five transparency-score rankings. The result shows that innovation (i.e., *R&D*, *PATENT*, and *CITATION*) increases monotonically as the transparency score increases. The difference between the two extreme quintiles is significant (p-value < 0.01). Firm-level

[9] The choice of five years is based on the averaged product development cycle (Brown et al., 2013; Hall, 2002); my results are robust to alternative time windows.
[10] Following Francis and Smith (1995), I also use the scaled percentile ranks of the innovation variables in OLS regression to mitigate the concern of skewness and the potential nonlinearities in the functional relation. In untabulated result, I find my results remain inferentially unchanged.

characteristics are summarized at the bottom part of panel B. The median values of *SMOOTH_RATIO* and *SMOOTH_CORR* are similar in magnitude to those reported by Lang et al. (2012). On average, each firm in the sample is followed by 4.29 analysts, and 20% of the sample firms prepare their financial statements under International Accounting Standards (*INT_GAAP*). My sample firms have a median value of total sales of $280.40 million and a median of 1,232 employees. On average, they are profitable, as evidenced by the mean value of *ROA* of 0.026, and have experienced 10.20% sales growth over recent years.

Table 2, panel A, presents the Pearson correlations among transparency component variables. Most transparency measures are significantly correlated in the expected direction, suggesting they capture a shared underlying construct. Panel B reports the Pearson correlations among selected variables. Most pair-wise correlations are significant in the expected direction at the 1% level. As expected, three innovation measures—*R&D*, *PATENT*, and *CITATION*—are highly correlated with one another. More importantly, *TRANS* is positively and significantly correlated with the measures of innovation (i.e., *R&D*, *PATENT*, and *CITATION*), providing univariate evidence on a positive relation between transparency and innovation.

[Insert Table 2]

4. Empirical Analyses and Regression Results

4.1. Test of H1a on Transparency and Innovative Effort

To test H1a, I estimate the following model (1) using a fixed-effect panel regression that links R&D in year *t*+1 to firm transparency measures as well as a set of control variables in year *t*:

$$R\&D_{ijt+1} = \beta_0 + \boldsymbol{\beta_1 Transparency_{ijt}} + \beta_k\, \Sigma Controls_{ijt} + Fixed\ Effects + \varepsilon_{ijt}, \tag{1}$$

where $R\&D_{ijt+1}$ is a measure of innovative effort captured by R&D intensity. $Transparency_{ijt}$ is proxied by individual transparency component or composite transparency. The subscripts *i*, *j*, and *t* denote firm, country, and time, respectively. In all regressions, I control for country-, industry-, and year-fixed effects so that my identification exclusively exploits *cross-sectional* variation of firm transparency and innovation *within* a specific country, industry, and year. Since my variable of interest, *Transparency*, is measured at the *firm*-level, I cluster standard errors at the firm level to account possible correlation in error terms (Lang et al., 2012; Petersen, 2009). A positive and significant β_1 will be consistent with H1a.

Table 3 reports the regression result of testing H1a. The individual transparency components are added sequentially from columns (1) through (6), and column (7) reports the results using composite transparency. Consistent with H1a, the first three measures—*SMOOTH_RATIO*, *SMOOTH_CORR*, and *ABS_ACCR*—are negatively associated with *R&D*, as they capture managerial discretion in financial reporting. In contrast, the other three transparency measures—*INT_GAAP*, *ANALYST*, and *ACCURACY*, which capture the use of global accounting standards and the quality of the external information environment—all exhibit significantly positive association with *R&D*.[11] The result remains consistent using *TRANS* in column (7). The effect is also economically meaningful. For example, the result in column (7) suggests that an interquartile shift from the 25th to the 75th percentile in *TRANS* is associated with a nearly 29% increase in *R&D*.[12] Consistent with H1a, this result suggests that transparency directly boosts managerial effort in R&D investment, over and above its indirect effect through external financing.[13]

[Insert Table 3]

Test of H1b: Transparency and the Sensitivity of Manager Turnover to Innovative Output

To test H1b on whether transparency encourages R&D effort by reducing the sensitivity of management turnover to (poor) innovative output, I follow prior research (e.g., Defond and Hung, 2004) and estimate the following logit regression model (2):

$$Pr\ (Turnover{=}1)_{ijt+1} = \beta_0 + \beta_1 Output_{ijt} + \beta_2 High\_Trans_{ijt} + \boldsymbol{\beta_3\ Output_{ijt} * High\_Trans_{ijt}}$$

[11] There are discrepancies in prior research with respect to the relation between analysts and innovation. He and Tian (2013) find analysts put "pressure" on firms, leading to lower innovation in the United States. However, as noted by Lang et al. (2012), analyst following can have different implications internationally. International studies find that analysts play an "information" role, gathering and aggregating information to assess firm value and improving overall transparency (Lang et al., 2012; Lang and Lundholm, 1996).

[12] Economic significance for R&D intensity is calculated as follows. From Table 1, Panel B, *R&D* has a mean value of 0.015 and an interquartile shift in *TRANS* leads to an increase of 0.227 (=0.013 − (−0.214)). The coefficient on *TRANS* in Table 3, column (7), is 0.019, and economic significance is calculated as (0.015+ (0.227*0.019))/0.015−1.

[13] Untabulated results show that, when *FINANCE* is excluded as a control, the magnitude of the coefficient estimate on *TRANS* only slightly increases from 0.019 to 0.020 with similar significance level, suggesting that external financing is unlikely to be the primary channel through which transparency promotes R&D investment.

$$+ \beta_k \, \Sigma \, Controls_{ijt} + Fixed \; Effects + \varepsilon_{ijt}, \tag{2}$$

where *Turnover* equals one for year t+1 if an important management team member announced a departure (excluding retirement) or was ousted and zero otherwise.[14] *Output* is captured by *PATENT* or *CITATION*. *HIGH_TRANS* equals to one if *TRANS* is above the sample median and zero otherwise. I include earnings (*ROA*), earnings changes (*ΔROA*), and stock return (*RET*) to control for standard firm performance as well as R&D investment to control for innovative input. The coefficient of β_1 is expected to be *negative* because low innovative output can result in higher likelihood of management turnover. To be consistent with H1b, β_3 is expected to be significant and *positive*, suggesting that higher transparency reduces the *sensitivity* of management turnover to (poor) innovative output. Note that Worldscope only provides employment data starting from 2002, so the sample to estimate model (2) is restricted to 10,256 firm-year observations.

Table 4 reports the results of testing H1b. Multicollinearity is more likely to be a concern in a nonlinear model (e.g., logit model). To assess this, I perform the diagnostic procedures recommended by Allison (1999) and find VIF scores of all my independent variables are lower than 2 and all tolerance statistics exceed the suggested cutoff of 0.4, suggesting that multicollinearity is unlikely to affect my results. For each analysis, I report both the baseline results without the transparency variable and the full model results with the interaction term *OUTPUT*HIGH_TRANS*. Note that both the logit coefficient estimate and *marginal* effect for each variable are reported.[15] As shown in column (1) and (2), the coefficient on *PATENT* is significant and negative, suggesting that managers are more likely to be replaced due to innovation failure, holding other firm performance measures constant. Turning to columns (3) and (4), I find that transparency significantly reduces the sensitivity of management turnover

[14] Worldscope does not further distinguish between a voluntary departure (other than retirement) and a forced one. However, this should not be a concern, since a significant amount of turnover labeled “voluntary” is in fact performance-induced. Thus an exclusive focus on “forced” turnover may create a downward bias in the estimated turnover-performance sensitivity (Kaplan and Minton, 2012).

[15] Coefficients in a logit model with interaction term are difficult to interpret directly due to nonlinearity (Ai and Norton, 2008). Thus I report marginal effects (the partial derivative of the logit function for variables of interest) and marginal effects for an interaction term (the cross-partial derivative for the two interacted variables). These partial derivatives are evaluated at the mean values of all variables and the statistical significance of the estimates is calculated based on standard errors of marginal effects using the Delta method (Ai and Norton, 2008; Greene, 2008).

to poor innovative output (interaction marginal effect is positive and statistically significant (p-value<0.05)), supporting the notion that transparency improves managers' innovative effort by mitigating their career concerns. In contrast, the coefficient of *PATENT* alone is significantly negative, suggesting that firms with *lower* transparency are *more* likely to dismiss managers when there is bad news about innovation.

To provide a sense of economic significance of the marginal effect of interaction term, in untabulated analysis, I follow Bushman et al. (2010) and partition my sample into quartiles based on transparency variable. Based on the estimates, a firm in the lowest quartile of transparency score has a 5.79% likelihood of management turnover, while an otherwise similar firm in the top quartile only has a 0.49% likelihood.[16] Using *CITATION* as an alternative measure of innovative output yields consistent results in column (4)–(6). In sum, the result in Table 4 is consistent with H1b and provides direct evidence on reduced career concerns as the main channel through which transparency improves managers' innovative effort.

[Insert Table 4]

Test of H1c: Cross-sectional Result on Career risk

I further exploit cross-section variation in the transparency-R&D relation conditional on career risk. To test H1c, I first partition my sample into two subgroups, based on the median cutoff of career risk proxies, and then re-estimate model (1) separately for each subsample and evaluate the coefficient difference in β_1 using an F-test. As noted by Lang et al. (2012), this approach allows the coefficient estimate of each explanatory variable (i.e., control variables and even fixed effects) to vary by partitioning variables in a fully interacted specification.[17] Two measures are used to capture the career risk of investing in R&D: the extent of shares held by insiders (*INSIDE_OWN%*) and the length of the product

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[16] Economic effect is calculated as the product of three terms: the coefficient estimate times mean turnover density (i.e., this product is the marginal effect reported in Table 4), times the standard deviation of the variable. The economic significance of my results is comparable to those of prior studies examining the performance/CEO turnover relation (e.g., Bushman et al., 2010; Engel et al., 2003)

[17] Results are very similar if I estimate a single regression with an interaction term between transparency and partitioning variables.

development cycle (*CYCLE*). Following Chang et al. (2013), I measure *CYCLE* as the industry-level R&D amortizable life, since products having longer development cycles generally have longer amortizable lives.[18]

As reported in Table 5, consistent with H1c, the coefficient estimates of transparency are significantly larger for firms with lower insider ownership and longer product development cycles, where managers are subject to higher career risks of investing in R&D. All controls are included but not reported for brevity. These cross-sectional results confirm the reduction of career concerns as the underlying mechanism through which transparency promotes managers' innovative effort.

[Insert Table 5]

4.2. Test of H2 on Transparency and Innovative Efficiency

To test H2a on the relation between firm transparency and innovative outcomes, I estimate the following fixed-effect panel regression model (3):

$$Outcome_{ijt+1} = \beta_0 + \boldsymbol{\beta_1 Transparency_{ijt}} + \beta_k \Sigma Controls_{ijt} + Fixed\ Effects + \varepsilon_{ijt}, \quad (3)$$

where $Outcome_{ijt+1}$ is proxied by either innovative *output* or innovative *efficiency*. In addition to output measures introduced in section 3.2, I also follow Hirshleifer et al. (2013) and calculate two measures to capture overall innovative *efficiency* in generating patents or citations per dollar of R&D investment. My first measure, *IE_PATENT*, is the number of patents scaled by R&D capital (*PATENT/RDC*), where *RDC* is calculated as $RDEXP_t + 0.8{*}RDEXP_{t-1} + 0.6{*}RDEXP_{t-2} + 0.4{*}RDEXP_{t-3} + 0.2{*}RDEXP_{t-4}$.[19] This measure is premised on R&D expenses over the preceding five years all contributing to successful patent applications filed in year t, assuming an annual depreciation rate of 20% of R&D capital over a five-year

[18] The data on amortizable lives are from Aswath Damodaran's website: http://people.stern.nyu.edu/adamodar/New_Home_Page/spreadsh.htm.

[19] Following Hirshleifer et al. (2013), I set missing R&D to zero in computing *RDC*. One slight difference between my innovative efficiency measure and theirs is that they lagged RDC by two years to allow a two-year lag between the patent filing date and grant date because they examine the stock market valuation of innovation outcomes and thus the data is constructed on the grant date. However, since my focus is a firm's ability to convert R&D capital into patents, I view patent filings as a more appropriate output of firm innovation in my setting. Research suggests that application year better captures the actual effective time of innovation (Griliches et al., 1988).

useful life (Chan et al., 2001; Lev et al., 2005).[20] Similarly, my second proxy, *IE_CITATION*, is the forward citations received by the patents applied for during a given year scaled by R&D capital (*CITATION/RDC*).

Table 6 presents the results of this analysis. Given the similarity of results using patent- and citation-based measures, only the former are reported for brevity. As shown in columns (1)–(7), regardless how transparency is measured, I find it is significantly and positively associated with *PATENT*, after controlling for *R&D*. This result suggests that transparency has a direct effect on innovative output over and beyond *its indirect effect through R&D investment*. Using *IE_PATENT* as an efficiency measure yields consistent results in column (8). The results (untabulated) are similar when considering the technological importance of the patent filings—I continue to find a significantly positive coefficient of *TRANS* (0.686, t-stat=5.90) on *IE_CITATION*. These results are also economically significant, for example, an interquartile shift from the 25th to the 75th percentile in *TRANS* is associated with nearly 26% and 25% increases in *IE_PATENT* and *IE_CITATION*, respectively.[21] In sum, the results in Tables 6 are consistent with H2a, showing that higher transparency is associated with both greater innovative output and efficiency.

[Insert Table 6]

Test of H2b: Transparency and the Sensitivity of R&D to the Investment Opportunity Set

To test H2b on the *source* of efficiency gain, I examine whether firm transparency increases the responsiveness of firms' R&D investment to the investment opportunity set by estimating model (4):

$$R\&D_{ijt+1} = \beta_0 + \boldsymbol{\beta_1 Q_{ijt}} + \beta_2 \, \mathbf{High\_Trans_{ijt}} + \beta_3 \, \mathbf{Q_{ijt}{*}High\_Trans_{ijt}} + \beta_k \Sigma \, Controls_{ijt} + Fixed\ Effects + \varepsilon_{ijt}, \quad (4)$$

[20] My results are also robust to three sensitivity tests: (1) assuming only contemporaneous R&D contributing to successful patent filings; (2) assuming an alternative amortization rate of 15 percent, following a highly influential database compiled on R&D activity by National Bureau of Economic Research (Hall et al., 1988), and (3) allowing the economic life of assets to vary by industry in calculating R&D capital by matching my sample to the estimate of corresponding economic life reported by Lev and Sougiannis (1996) based on two-digit SIC code.

[21] The economic significance of transparency on innovative efficiency is calculated as follows. The coefficient of *TRANS* in Table 6, column (8), is 0.475, and the mean value of *IE_PATENT* is 0.4245, and the economic significance is calculated as (0.4245+ (0.227*0.475))/ 0.4245−1. Likewise, in untabulated results, the coefficient of *TRANS* on *IE_CITATION* is 0.686, and the mean value of *IE_CITATION* is 0.6216, and the economic significance is calculated as (0.6215+ (0.227*0.686))/ 0.6215−1.

where Tobin's q (*Q*) is a measure of investment opportunity set (Skinner, 1993). All other variables are defined as before. The coefficient of interest β_3 captures the differential effect of R&D responsiveness to the investment opportunity set conditional on firm transparency. A significant and positive β_3 will be consistent with H2b in that transparency increases the sensitivity of R&D to the investment opportunity set.

The baseline result in Table 7, Column (1), shows a significant and positive coefficient on *Q*, confirming, on average, a positive R&D-investment opportunity relation. I then add transparency and its interaction term with *Q* in Column (2). Consistent with H2b, *Q*HIGH_TRANS* is significantly positive (*p*-value<0.01), suggesting that firms with greater transparency exhibit higher responsiveness of R&D to the investment opportunity set. These results provide evidence on the *source* of the efficiency gain from transparency by pointing to its governance role in facilitating more efficient allocation of R&D capital.

[Insert Table 7]

Test of H2c and H2d: Cross-sectional Result on Monitoring Demand or Proprietary Cost

I further explore cross-sectional variation in the transparency-innovative efficiency relation, conditional on monitoring demand and proprietary cost. To test H2c, I use firm-level organizational complexity (*COMPLEXITY*) and country-level governance regime (*RULE_LAW*) to capture monitoring demand. *COMPLEXITY* is measured by the number of geographic and business segments of a given firm and year (e.g., Bushman et al., 2004a; Engel et al., 2010). *RULE_LAW*, reflecting perceptions of the extent to which agents have confidence in and abide by the rules of society, is a commonly used measure of the strength of governance regime (e.g., La Porta et al., 1998). The results in Table 8, Panel A, are consistent with H2c, showing that firm transparency is particularly important in facilitating innovative efficiency for firms with greater organizational complexity and in countries with relatively weak governance regimes.

To test H2d on the role of proprietary cost of transparency, I rely on the strength of property rights protection (*PROPERTY_RIGHTS*) and contract enforceability (*ENFORCE*) to capture proprietary costs.[22] *PROPERTY_RIGHTS* is a composite index calculated based on five property indexes introduced by Claessens and Laeven (2003). *ENFORCE* is an index developed by Djankov et al. (2003) to capture the enforcement strength of contracts. As shown in Table 8, Panel B, consistent with H2d, the *positive* effect of *TRANS* on innovative efficiency is *offset* for firms in countries with weak property rights and contract enforceability, where proprietary cost of transparency is higher.

[Insert Table 8]

5. Endogeneity and Identification Strategies

Given the endogenous nature of accounting disclosure, an observed association between transparency and innovation may be driven by omitted, correlated variables or reverse causality. The inclusion of country-, industry-, and year-fixed effects in my main analyses ensures that the identification of my results comes from cross-sectional variation of transparency *within* a given country, industry, and year and cannot be attributed to unobservable cross-country differences (e.g., legal institutions, political regime, accounting norms, etc.). Moreover, the robustness to *firm-fixed* effects or *Country*Year* fixed effects (discussed in section 6.1) makes it unlikely my results are simply driven by cross-firm heterogeneity or country-level macroeconomic shocks (e.g., changes in tax laws). Lastly, if the concerns are that transparency and innovation are both high because a firm is facing greater market competition, seeing global expanding opportunity or trying to obtain favorable valuation, inclusion of control variables, such as firm size, the Herfindahl index, the market-to-book ratio, foreign sales, cross-listing status, and sales growth, should mitigate this concern. To provide greater assurance, I adopt the following strategies to formally address omitted variables and reverse causality.[23]

5.1. Omitted Variable: Single-Country Analysis using the U.S. Sample

[22] Legal protection of property rights alone provides an imperfect safeguard against resource expropriation and underinvestment problems, because the level of legal protection is largely characterized by the enforceability of underlying contracts (Shleifer and Vishny, 1997).

[23] In an untabulated test, I also implement a 2SLS regression using number of business segments as an instrumental variable for transparency (Bushman et al., 2004a) and find confirmatory evidence. My instrumental variable is significantly associated with firm transparency but not theoretically related to innovation. However, as noted by Lang and Maffett (2011), the 2SLS approach is difficult to apply to research in transparency, because it is hard to identify variables that are truly exogenous. I thus consider the 2SLS result as an indication for the robustness of my findings.

One common concern for international studies is the unobservable, omitted variables at the country-level. In addition to controlling for country fixed effects, I conduct a supplementary single-country analysis using only the U.S. firms. This analysis provides two major benefits. First, by holding the institutional details and accounting standards constant for all firms, I only exploit *within* country cross-sectional variation of firm transparency on innovation, over and above the general effects of country-level institutional factors. Second, a focus on U.S. firms allows me to eliminate the potential bias of USPTO in capturing patenting activities of foreign firms.

Table 9 reports the results for this single-country analysis. Columns (1), (3), and (5) report the results using industry- and year-fixed effects. I find consistent evidence on both innovative effort and efficiency based on the U.S. sample, and the coefficient magnitudes of transparency variable are comparable with those of my main results in Tables 3 and 6. The results remain robust after controlling for *firm*- and year-fixed effects in columns (2), (4), and (6). This single-country analysis corroborates my main findings and suggests that time-invariant cross-country differences are unlikely to drive my results.

[Insert Table 9]

5.2. Reverse Causality: Difference-in-Differences Approach using Mandatory IFRS Adoption

An ideal setting to address reverse causality is to identify an exogenous shock to transparency unrelated to firm innovation. *Mandatory* IFRS adoption in 2005 provides a natural setting for identifying the exogenous improvement of transparency for at least two reasons. First, widespread adoption of IFRS represents one of the most significant time-series changes in accounting and substantially impacts firm transparency (Ashbaugh and Pincus, 2001; Barth et al., 2008), through improving earnings quality (Barth et al., 2008) and reducing information asymmetry (Daske et al., 2013).[24] Second, since individual firms themselves had little control over a country's decision to mandate IFRS, this requirement potentially represents an *exogenous* shock to firms' information environment.

[24] I do not stipulate that IFRS adoption per se leads to an improvement in firm transparency but rather that it proxies for country-level (regulatory) concurrent changes in *financial reporting* enforcement (e.g., insider trading laws, filing requirement, and transparency directives) related to financial reporting. As noted by Christensen et al. (2013), many of these contemporaneous enforcement changes also served to decrease information asymmetry and thus likely represented shocks to firm-level transparency.

To evaluate the overall effect of mandatory IFRS adoption, I estimate the following difference-in-differences model to compare the change in innovation between the treatment and control samples before and after the shock:

$$Innovation_{ijt}=\beta_0 + \beta_1 POST_{ijt} + \beta_2 IFRS_{ijt} + \boldsymbol{\beta_3 POST_{ijt}*IFRS_{ijt}} + \beta_4 Controls_{ijt} + Fixed\ Effects + \varepsilon_{ijt}, \quad (5)$$

where *Innovation* is proxied by either innovative effort or innovative efficiency. *POST* is coded as one for post-IFRS period and zero for the pre-IFRS period.[25] Adoption year *t* in this study is 2005 (2006) for firms with a December (non-December) fiscal year-end. *IFRS* is equal to one for firms in the *treatment* sample and zero for firms in the *control* sample. The treatment sample consists of *mandatory* adopter firms in EU countries. My benchmark control sample consists of only *non-IFRS adopters*, because it eliminates the potential self-selection bias associated with either voluntary adopters or late adopters, and fully controls for contemporaneous time effects unrelated to mandatory IFRS adoption (Defond et al., 2011).

As reported in Table 10, irrespective of the dependent variables, I find that the coefficient of interest β_3 are consistently significant and positive (p-value<0.01), suggesting mandatory adopters experienced a significantly larger increase in innovative effort and efficiency, relative to non-adopters before and after. My results are also robust to three alternative time windows: [t−1, t+3], [t−3, t+3], and [t−5, t+5]. One potential concern is that country-level change in *legal* enforcement around mandatory IFRS adoption may be correlated with changes in innovation. To address this, I downsize my treatment sample by excluding firms in any country that is identified as having bundled enforcement changes with the adoption of IFRS (i.e., firms from the five EU countries—Finland, Germany, Netherlands, Norway, and the United Kingdom) and rerun the earlier tests. If my original results are driven by policy bundling, I should not observe significant differences in innovation between treatment and control firms in the remaining EU countries. My results (untabulated) remain strong.

[Insert Table 10]

[25] Following DeFond et al. (2011), I omit the year of mandatory adoption, 2005, to avoid confounding effects in the transition year, as it is not clear whether investors fully understood IFRS-compliant financial statements or whether preparers applied the new rules appropriately.

5.3. Reverse Causality: Change Model and Dynamic Analysis using Lead and Lag Design

To further tackle reverse causality, I adopt two other strategies. (1) I estimate a *change-on-change* model to examine the effects of changes in transparency (*ΔTRANS*) in year t on subsequent changes in innovation (*ΔINNO*) in year t+1 (Finkel, 1995). (2) I analyze the details of dynamic changes in transparency (*ΔTRANS*) on changes in innovation (*ΔINNO*) by including three-year lead and lag value of *ΔTRANS* in the model. This dynamic analysis is widely used in the financial economic research to address reverse causality (e.g., Louis and Urcan, 2017; Simintzi et al., 2014). The idea is that, if transparency drives innovation, we should observe only lag changes in transparency associated with *future* change in innovation but lead changes in transparency should *not* be associated with *past* change in innovation.

Table 11 reports the results of both analyses. Columns (1)–(2) and (3)–(6) report the results for innovative effort and efficiency, respectively. Column (1) presents the results of change analysis, which confirms that changes in transparency (*ΔTRANS*) in year t lead to subsequent changes in R&D investment (*ΔR&D*) in year t+1 (p-value<0.05). The results of dynamic analysis in column (2) provides confirmatory evidence that, while the lag changes in *ΔTRANS* are positively associated with *future* changes in R&D investment, the lead changes in *ΔTRANS* are *not* associated with *past* changes in R&D investment. Similar results are also documented in columns (3)–(6), when *IE_PATENT* or *IE_CITATION* is used as the dependent variable. Overall, the robustness to the lead-lag analyses, combined with the difference-in-differences approach, suggest that transparency is a driver of innovation, as opposed to innovation being the driver of transparency, mitigating the concerns of reverse causality.[26]

[Insert Table 11]

5.4. Cross-sectional Correlation in Error Terms: Clustering by Country and Within-Country Regressions

One concern of a pooling regression across countries is that it may create cross-sectional correlation among the error terms, resulting in overstated statistics. To mitigate this concern, I adopt two

[26] As an untabulated sensitivity analysis, I follow Verdi (2006) and repeat the main analyses by explicitly controlling for up to three lags of past innovation in the model. If it is past innovation which drives firms' transparency choices, then there should be no relation between transparency and *future* innovation after controlling for *past* innovation. I find that transparency remains a significant predictor for future innovation, after controlling for past innovation.

strategies. First, I cluster standard errors at the *country*-level (Christensen et al., 2013). This analysis corrects for within-country correlations by treating each country as a separate cluster. I find my inferences remain unchanged. Second, I conduct *within-country* regressions to compute the t-statistics equal to the mean of the estimated coefficients for each country, divided by the standard error of the coefficients. Because these statistics are based on the coefficients from the *within* country regressions, they are unaffected by the potentially inflated t-statistics in the pooled regressions. Estimating model (1) within each of the 29 countries, I find that the coefficient of transparency on *R&D* is positive in 25 countries (20 significant (two tailed), 23 significant (one tailed)). The averaged coefficient estimate of *TRANS* remains significantly positive (average coefficient=0.019, t-stat=7.60, p-value<0.01). I next turn to innovative efficiency test by estimating model (3) within each of the sample country. Among the 24 countries that have nonmissing values for calculating innovative efficiency measures, the coefficient of transparency on *IE_PATENT* is positive in 20 countries (12 significant (two-tailed); 15 significant (one-tailed)). The averaged coefficient estimate of *TRANS* on *IE_PATENT* remains significantly positive (average coefficient=0.232, t-stat=2.75, p-value<0.05). The analysis on *IE_CITATION* yields a similar result (average coefficient=0.339, t-stat=2.61, p-value<0.05).

To control for potential cross-sectional correlation *within years*, I repeat the analysis within each of the 20 years (1990–2010) in the sample and find that the coefficient on *TRANS* is significantly positive in *every* year out of 20 years (10 significant (two-tailed); 13 significant (one-tailed)). Overall, these results confirm the consistency of my main findings across a wide range of countries and time periods.

6. Robustness Tests

*6.1. Controlling for Country*Year, Firm-Fixed Effects and Firm-level Shocks*

Given the inclusion of country-fixed effects in my main analyses, my results would be biased only if *time-varying* country-level macroeconomic shocks (e.g., changes in tax laws) or time-invariant cross-firm heterogeneity that affect innovation are also correlated with the changes in firm transparency. To address this, I include *country*year* and *firm-fixed* effects in the model. Furthermore, to account for the possibility that firm-level shocks, such as firms' growth opportunities and financing needs, may *simultaneously* affect both firm innovation and transparency, I follow Lang et al. (2012) and explicitly control for four *forward-looking* variables. I include analysts' long-term growth forecasts and period t+1 sales growth (assuming perfect foresight) to capture predictable changes in firm growth opportunities; I also include capital raising and capital expenditures in period t+1 to control for shocks to a firm's financing needs. My results (untabulated) remain robust and consistent across all specifications, suggesting that they are unlikely driven by macroeconomic shocks, time-invariant cross-firm heterogeneity, or *managerial foresight* of growth opportunities and financing needs.

6.2. Controlling for Patenting Incentive Biases

Firms may have differing incentives to patent with USPTO. I tackle this issue in a number of ways. First, I cross-check my findings by bringing in new patent data from European Patent Office (EPO), which arguably better captures the patenting activities for firms in EU countries. Second, I follow Acharya et al. (2013) by directly controlling for country-level determinants of patenting with USPTO: the extent of bilateral trade that a country has with the United States and a country's comparative advantages.[27] Third, patenting incentive may also vary by the nature of innovation. Research suggests that, compared to those with product-oriented innovation, industries with *process-oriented* innovation may have less incentive to file patents since it is more difficult to track imitations of processes (Arundel and Kabla, 1998; Brouwer and Kleinknecht, 1999). Thus I follow Cohen and Klepper (1996) and add industry-level average process share (%) as an additional control. Lastly, I further include *industry*year* fixed effects to fully absorb industry technological shocks. The robustness and consistency across all these analyses suggest that my results cannot be explained by potential patenting incentive biases.

6.3. Dealing with Missing Values and Reporting Bias of R&D

While R&D is the most widely used measure for innovative effort, it is potentially subject to measurement errors. For one, missing R&D does not necessarily mean that the firm lacks innovative

[27] Specifically, I (1) add, for each country, the logarithm of the levels of imports and exports that the country has with the United States in each year at each three-digit ISIC industry level, using data from Nicita and Olarreaga (2007), and (2) employ industry-level comparative advantage as the ratio of value added in a three-digit ISIC industry to the total value added by that country in a given year. The SIC-ISIC concordance data is shared by Jon Haveman.

activity (Koh and Reeb, 2015). I repeat my main analysis by (1) replacing missing R&D with the industry-level average, as suggested by Koh and Reeb (2015), and (2) restricting my sample to observations with nonmissing values for R&D. Moreover, reported R&D is sensitive to accounting standards (He and Tian, 2013). I conduct a single country analysis using the U.S. sample (in section 5.1) and a separate examination for EU countries (capitalizers) and non-EU countries (expensers).[28] Lastly, R&D may also be subject to managerial manipulation (Lev et al., 2005). To alleviate this concern, I adopt four approaches, including using average percentile ranking of R&D, excluding suspect firms (i.e., those that just meet or beat earnings benchmarks (less or equal to 0.01) and report contemporaneous R&D reduction) (Graham et al., 2005; Lev et al., 2005), estimating predicted value of R&D (Skaife et al., 2013), and using three-year average of R&D to capture the long-run effect. In untabulated results, I find the coefficients on *TRANS* are consistently positive and statistically significant across all these analyses.

If R&D misreporting is present in my data, I would expect that, on average, a conservative OLS estimate of transparency to the extent that reported R&D are downward biased. Notably, the attenuation bias does not distort the sign of this relationship, and it does not lead to spurious findings of a significant relationship if there is none. While the measurement error may introduce noise into R&D, it should not impart any systematic bias to my results.

6.4. Controlling for Firm-level Institutional Ownership

Several studies suggest that institutional shareholders help promote firms' long-term investment, including innovation (Aghion et al., 2013; Bena et al., 2016). I obtain institutional holdings data from the FactSet/LionShares database for the period 2000–2010 and merge it with my sample at the firm-year basis. I find my results remain strong after controlling for institutional ownership, suggesting that transparency has an important and distinct effect on innovation, over and beyond conventional governance mechanisms.

6.5. Mitigating Large Sample Biases

[28] The revised International Accounting Standards (IAS) 38 adopted in the European Union allows for partial capitalization of R&D if certain criteria are met.

To ensure my results are not sensitive to the sample selection, I exclude some leading innovative countries (i.e., Japan and United Kingdom) from the sample. Untabulated results show that the coefficient on transparency remains significantly positive (*p*-value<0.01). As a more general approach, I implement a weighted least squares model in which the number of observations per country are used as weights. My results remain strong and consistent across all innovation measures.

6.6. Alternative Measures using Truncation-adjusted Patents and Citations

The truncation bias in patent grants stems from the lag in patent approval (about two years). Toward the end of the sample, patents are underreported, since many patents might not have been granted yet. To address this, I re-estimate the regression based on a subsample from 1990 to 2007, three years before the end of the patent data. In addition, I follow Hall et al. (2001) and calculate the application-grant year distribution for period of 1990–2000 and then compute the truncation-adjusted patent counts for the period of 2001–2010 by dividing raw patent counts by adjustment factor.[29] While both strategies substantially reduce the sample size, my inferences remain unchanged.

7. Concluding Remarks

Innovation is a key driver of economic growth and firm competitiveness. Yet few studies examine whether and how a firm's information environment impacts its technological development. To my knowledge, my study is the first to systematically explore the role of firm transparency in innovation and unravel the mechanisms through which these effects occur. Constructing a novel international firm-patent matched panel database from 29 countries, I provide strong evidence that transparency directly increases managers' effort in investing in R&D by reducing their career concerns; it also enhances the efficiency of converting R&D to patents (or citations) through facilitating efficient resource allocation. Exploiting cross-country variation in intellectual property rights protection, my study also illuminates the proprietary cost of transparency in moderating its relation with innovation.

[29] The application-grant lag distribution (W_s) is calculated as the percentage of patents applied for in a given year that are granted in *s* years. The truncation-adjusted patent counts, P_{adj}, are computed as $P_{adj}=P_{raw}/\sum_{s=0}^{2010-t} Ws$.

Given the increasing importance of innovation to the global economy, my findings can inform both academics and firms. My study contributes to the literature on the real effects of accounting by providing insights into the consequences of the firm information environment on innovation incentives and outcomes. If career risks curb managers' incentive to innovate, this study provides new evidence on how the implicit contracting role of firm transparency may mitigate this problem and promote innovative effort. Moreover, since firm survival critically depends on the ability to innovate efficiently, my study uncovers the source of the efficiency gain by highlighting the governance role of transparency in facilitating more efficient flow of R&D capital to investment opportunity. It also informs firms about the potential proprietary costs of transparency, especially when country-level property rights are weak.

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Appendix A. Variable Descriptions

Variables	Description
Dependent variables	
R&D	=Research and development expenditures scaled by total assets
PATENT	=Natural log of one plus total number of patents applied by firm in a given year
CITATION	=Natural log of one plus total number of citations summed across all patents applied by firm in a given year
IE_PATENT	=Natural log of one plus total number of patents applied by a firm in a given year scaled by R&D capital (*RDC*). *RDC* is calculated as $RDEXP_{t}$+ 0.8*$RDEXP_{t-1}$+ 0.6*$RDEXP_{t-2}$ + 0.4*$RDEXP_{t-3}$ + 0.2*$RDEXP_{t-4}$, where *RDEXP* equals annual R&D expense
IE_CITATION	=Natural log of one plus total number of citations summed across all patents applied by a firm in a given year scaled by R&D capital (*RDC*). *RDC* is calculated as $RDEXP_{t}$+ 0.8*$RDEXP_{t-1}$ + 0.6$RDEXP_{t-2}$ + 0.4*$RDEXP_{t-3}$ + 0.2*$RDEXP_{t-4}$, where *RDEXP* equals annual R&D expense
TURNOVER	=A dummy variable that takes the value of one for a given year if an important management team member announced a departure (excluding retirement) or was ousted and zero otherwise
Test variables	
TRANS	=A composite measure of transparency, calculated as the average of the scaled percentile rank of six variables: *INT_GAAP*, *ANALYST*, *ACCURACY*, (1-*SMOOTH_RATIO*), (1-*SMOOTH_CORR*) and (1-*ABS_ACCR*), with higher values indicating greater transparency. If *ACCURACY* is unavailable, *TRANS* captures the average percentile rank of the remaining five variables.
SMOOTH_RATIO	=Product of (-1) times the standard deviation of income before extraordinary items (scaled by average total assets) divided by the standard deviation of cash flows (scaled by average total assets), where standard deviation is computed over a minimum of three and maximum of five year rolling window. Higher values indicate lower transparency.
SMOOTH_CORR	=Product of (-1) times the correlation between change in cash flow from operations (scaled by average total assets) and change in total accruals(scaled by average total assets), where correlation is computed over a minimum of three and maximum of five years of data. Higher values indicate lower transparency.
ABS_ACCR	=Magnitude of total accruals calculated as absolute value of accruals scaled by absolute value of the cash flow from operations. Higher values indicate lower transparency.
INT_GAAP	=An indicator variable that equals to one if the firm reports under IFRS or U.S. GAAP during the year, the zero otherwise. Higher values indicate greater transparency.
ANALYST	=Total number of analysts making a forecast for year t's earnings. Higher values indicate greater transparency.
ACCURACY	=Product of (-1) times the absolute value of the forecast error scaled by beginning stock price, where the forecast error is the I/B/E/S analysts' mean annual earnings forecast less the actual earnings as reported by I/B/E/S. Higher values indicate greater transparency.
Control variables	
Firm-level controls	
FINANCE	=The sum of a firm's net equity issues (scaled by total assets) over a rolling five-year window ending in the current fiscal year. Higher values indicate greater access to external financing.
SALES	=Natural log of sales in thousands of US$
EMPLOYMENT	=Natural log of one plus total number of employees in thousands
MTB	=Market value of equity divided by book value of equity
CLOSE%	=Total number of closely held shares as a percentage of the total number of shares outstanding
K/L	=Ratio computed as net property, plant and equipment scaled by total number of employees
SALES_GROWTH	=Annual change in net sales scaled by beginning total assets
ROA	=Net income before extraordinary items and preferred dividends scaled by beginning total assets
FIRM_AGE	= Natural log of one plus the number of years listed on Worldscope
LEV	=Total liabilities scaled by total assets
CASH	=Internally generated cash computed as after-tax income before extraordinary items plus depreciation and amortization plus R&D expense
HERFINDAHL	=Industry Herfindahl index based on all firms within each country, where industries are defined by 3-digit SIC code

FOREIGN_SALE%	=The percentage of foreign sales to total sales during past five years
ADR	=An indicator variable that equals to one if a firm is cross-listed in the U.S., zero otherwise.
ΔROA	=Change in net income before extraordinary items and preferred dividends scaled by beginning total assets
RET	=Market-adjusted stock returns over the fiscal year for a given firm
Q	=Book value of assets+ (market value of equity-book value of equity)/book value of assets. It reflects the valuation placed on the assets by the market relative to their book value
Country-level controls	
GDP	=The natural log of total gross domestic product (current US$). Source: The World Bank World Development Indicators
PERCAPITA	=The natural log of per capita gross domestic product (current US$). Source: The World Bank World Development Indicators
MKT_SIZE	=Stock market capitalization as a percentage of GDP. Source: The World Bank World Development Indicators
Country-level partitioning variables	
Property rights protection	
PROPERTY_FREEDOM	=A rating of property rights in each country (on a scale from 1 to 5), with higher values indicating greater protection over private property. The score is based on the degree of legal protection of private property, the probability that the government will expropriate private property, and the country's legal protection of private property. The index equals the median rating for the period 1990 to 2014. Source: The Index of Economic Freedom from the Heritage Foundation
PROPERTY_301	=An index of intellectual property rights (on a scale from 1 to 5), with higher values indicating greater protection. The index is calculated using the "Special 301"placements of the Office of the U.S. Trade Representative (USTR) special 301 requires the USTR to identify those countries that deny adequate and effective protection for intellectual property rights or deny fair and equitable market access for persons that rely on intellectual property protection. The following ratings are assigned: 1=Priority foreign countries; 2=306 Monitoring; 3=Priority watch list; 4=Watch list; 5=Not listed. The index equals the median rating for the period 1990 to 2013.
PROPERTY_PATENT	=An index of property rights (on a scale from 0 to 5) in 1980, with higher values indicating greater protection over patent rights. The index criteria are: coverage, membership, duration, enforcement and loss of rights.
PROPERTY_WEF	=An index of property rights (on a scale from 1 to 7) in 2013, with higher values indicating greater protection over intellectual property. Source: Global Competitiveness Report, World Economic Forum (2013)
PROPERTY_ICRG	=An index of property rights (on a scale from 0 to 10) based on the average rating between 1982 and 1995.The score is based on the average of five measures: quality of the bureaucracy, corruption in government, rule of law, expropriation risk, and repudiation of contracts by the government. Source: International Country Risk Guide and Knack and Keefer (1995)
PROPERTY_RIGHTS	=A composite measure of property rights protection calculated as (*PROPERTY_FREEDOM* /5) + (*PROPERTY_301* /5) + (*PROPERTY_PATENT* /5) + (*PROPERTY_WE* F/7) + (*PROPERTY_ICRG* /10). Higher values indicate greater property rights protection.
Contract enforceability	
ENFORCE	=Enforceability of contract, measured as number of days to resolve a payment dispute through courts. Higher values indicate stronger enforceability of contract. Source: Djankov et al. (2003)
Governance regime	
RULE_LAW	=Reflects perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts. Higher values indicate stronger corporate governance. Source: La Porta et al. (1998)
Firm-level partitioning variables	
INSIDE_OWN%	=Total number of shares held by insiders as a percentage of the total number of shares outstanding
CYCLE	=Product development cycle, measured as the industry-level R&D amortizable life. Source: Aswath Damodaran's website: http://people.stern.nyu.edu/adamodar/New_Home_Page/spreadsh.htm.
COMPLEXITY	=Number of geographical and business segments for a given firm and year, with higher values indicating greater organizational complexity.

Appendix B. Algorithm for firm-patent name matching

This appendix describes the algorithm I use to match USPTO patent assignees to firms in the Worldscope database. In the first step, I construct two datasets containing a complete set of assignee names from the USPTO and company names from Worldscope database from 1990 to 2010. From patent data compiled by Lai et al. (2011) through the Harvard database, I obtain the set of assignee names listed on the patent grant issued by the USPTO. The data set contains information about the assignee's country and the indicator of its status: U.S. corporation, non-U.S. corporation, or other. As my sample is restricted to foreign firms, I only use patents where at least one patent assignee is a non-U.S. corporation. For each firm in Worldscope, I compile the list of all names used by firms, including their current name and historical names. I also collect the firm's country of incorporation.

In the second step, I standardize both patent assignee names and firm names using regular expression language. My standardization focuses on the three main aspects of firm names.

1. Firm names contain only a–z, A–Z, and 0–9 characters. All other non-alphanumeric characters (e.g., % * @# ! etc.) are deleted.
2. Suffixes of firm names are unified. For example, firms with "1000," "2000," or "suspend" suffixes are standardized to only contain nonsuffix part of the name. To minimize the probability of mistakenly changing the firm name, this procedure is country specific.
3. Non-unique parts of firm names are shortened. For example, the word "CORPORATION" is abbreviated to "CORP." I also take into account all possible misspellings of this word, e.g., "COPRPORATION," "CORPOIRATION," "CORPORTATION," "COROPORTION," or "CORPOORATION." Similarly, "LIMITED" and "INCORP" are abbreviated "LTD" and "INC," respectively. This step makes unique elements of firm names longer, relative to their overall length, which increases the efficiency of the matching described next.

In the third step, I match each assignee name with current name or historical names of Worldscope firms using the Bigram string comparison algorithm.[30] I also impose a condition that the firm's country of incorporation obtained from Worldscope is the same as the assignee's country recorded in USPTO data. The Bigram comparison function is coded to return a value between 0 and 1, which accounts for the total number of bigrams that are common between the two strings divided by the average number of bigrams in the strings. For name pairs with a Bigram score above 0.5, I also compute the generalized Levenshtein edit-distance between the two names. Intuitively, the Levenshtein distance

[30] The Bigram algorithm compares two strings using all combinations of two consecutive characters within each string. For example, the word "bigram" contains the following bigrams: "bi," "ig," "gr," "ra," and "am." It is extremely effective for my purposes since it handles misspellings, omission of characters, and the swapping of words in the string.

between two strings is the minimum number of single-character edits (insertion, deletion, substitution) required to change one string into the other. Using both measures, I identify the closest Worldscope firm name for each patent assignee and then decide whether the assignee was matched to a Worldscope firm. These steps result in a database that links USPTO patent numbers to Worldscope firm codes.

I perform extensive checks on the standardization-matching algorithm. First, to find closest matches, I use different thresholds for the Bigram score and the Levenshtein edit distance. Second, I employ a different fuzzy matching algorithm (e.g., SPEDIS distance) to identify the closest matches other than the Bigram comparison function. These alterations only have limited impact on the matching outcome: assignments of less than 5% of patents in my data are affected.

Table 1 Sample Distribution and Summary Statistics

Panel A: Sample distribution by Country

	Firm-year obs.		*Unique firms*	
Country	*Number*	*Percent*	*Number*	*Percent*
Argentina	84	0.09%	14	0.11%
Australia	4222	4.76%	947	7.32%
Austria	412	0.46%	65	0.50%
Belgium	684	0.77%	95	0.73%
Brazil	539	0.61%	138	1.07%
Canada	2641	2.98%	684	5.29%
Chile	426	0.48%	75	0.58%
Denmark	1259	1.42%	149	1.15%
Finland	1436	1.62%	143	1.11%
France	5694	6.42%	708	5.48%
Germany	4017	4.53%	573	4.43%
Greece	364	0.41%	123	0.95%
India	3428	3.87%	911	7.05%
Indonesia	2353	2.65%	282	2.18%
Ireland	671	0.76%	85	0.66%
Israel	413	0.47%	92	0.71%
Italy	1788	2.02%	269	2.08%
Japan	20081	22.64%	1926	14.90%
Korea	4221	4.76%	828	6.40%
Malaysia	2809	3.17%	642	4.97%
Netherlands	1802	2.03%	219	1.69%
Norway	1386	1.56%	201	1.55%
Pakistan	211	0.24%	49	0.38%
Singapore	1524	1.72%	428	3.31%
South Africa	1829	2.06%	236	1.83%
Spain	882	0.99%	130	1.01%
Sweden	2159	2.43%	274	2.12%
Switzerland	1807	2.04%	218	1.69%
United Kingdom	19545	22.04%	2426	18.76%
All foreign firms	88687	100.00%	12930	100.00%

Table 1, panel A reports the sample distribution by country during 1990 to 2010.

Table 1 Sample and Summary Statistics

Panel B: Firm-level descriptive statistics

Innovation measures

Variable	**Obs.**	**Mean**	**Median**	**Std. Dev.**
R&D	88687	0.015	0.000	0.039
PATENT (raw)	88687	0.643	0.000	9.713
CITATION (raw)	88687	6.560	0.000	145.894

Mean R&D, PATENT and CITATION by firms' transparency score

Transparency ranking	*N*	*R&D*	*PATENT (raw)*	*CITATION (raw)*
Lowest	17824	0.009	0.309	2.114
2	17680	0.011	0.416	3.354
3	17717	0.016	0.611	5.937
4	17852	0.017	0.762	8.901
Highest	17614	0.023	1.113	12.480
Highest-Lowest	-	0.01	0.80	10.37
(*p* -value)	-	(<0.01)	(<0.01)	(<0.01)

Firm characteristics

Variable	**Obs.**	**Mean**	**Median**	**Std. Dev.**
TRANS	88687	-0.113	-0.095	0.171
SMOOTH_RATIO	88687	-0.423	-0.398	0.274
SMOOTH_CORR	88687	0.928	0.976	0.136
ABS_ACCR	88687	0.921	0.558	1.525
INT_GAAP	88687	0.200	0.000	0.400
ANALYST	88687	4.290	1.000	6.224
ACCURACY	56114	-0.101	-0.007	1.297
FINANCE	88687	0.149	0.016	0.319
SALES (US$ mln)	88687	1562.471	280.393	4560.119
EMPLOYMENT(#)	88687	7.614	1.232	26.736
MTB	88687	2.206	1.430	2.852
CLOSE%	88687	0.455	0.425	2.726
K/L	88687	5.874	4.901	3.294
SALES_GROWTH	88687	0.102	0.049	0.307
ROA	88687	0.026	0.045	0.143
FIRM_AGE	88687	2.437	2.565	0.846
LEV	88687	0.224	0.198	0.187
CASH	88687	0.032	0.075	0.309
HERFINDAHL	88687	0.425	0.341	0.310
FOREIGN_SALE%	88687	0.177	0.000	0.363
ADR	88687	0.085	0.000	0.278
GDP	88687	27.745	27.948	1.165
PERCAPITA	88687	9.980	10.324	0.994
MKT_SIZE	88687	82.917	70.556	60.528

Table 1, panel B reports descriptive statistics at the firm-level based on all firm-year observations between 1990 and 2010.All variables are defined in Appendix A.

Table 2
Pearson Correlations (*N*=88687)

Panel A: Correlation matrix of transparency components

	SMOOTH_RATIO	*SMOOTH_CORR*	*ABS_ACCR*	*INT_GAAP*	*ANALYST*	*ACCURACY*
SMOOTH_RATIO						
SMOOTH_CORR	**0.42**					
ABS_ACCR	**0.03**	0.00				
INT_GAAP	**-0.04**	**-0.02**	**-0.03**			
ANALYST	**-0.05**	**-0.03**	**-0.04**	**0.11**		
ACCURACY	**0.02**	0.01	0.00	**-0.01**	**0.02**	

Panel B: Correlation matrix of selected variables

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	*R&D*																				
2	*PATENT*	**0.09**																			
3	*CITATION*	**0.11**	**0.94**																		
4	*TRANS*	**0.12**	**0.04**	**0.04**																	
5	*FINANCE*	**0.21**	**-0.06**	**-0.06**	**0.03**																
6	*SALES*	**-0.15**	**0.14**	**0.14**	**0.26**	**-0.43**															
7	*EMPLOYMENT*	**-0.12**	**0.13**	**0.13**	**0.28**	**-0.37**	**0.86**														
8	*MTB*	**0.15**	0.00	0.00	**0.11**	**0.17**	**-0.05**	**-0.03**													
9	*CLOSE%*	**-0.01**	0.00	0.00	**-0.02**	**-0.01**	**-0.01**	**-0.02**	-0.01												
10	*K/L*	**-0.13**	**0.12**	**0.13**	**-0.23**	**-0.24**	**0.23**	**0.05**	**-0.17**	**0.02**											
11	*SALES_GROWTH*	**-0.03**	**-0.03**	**-0.03**	0.00	**0.07**	**0.01**	**-0.01**	**0.20**	**0.00**	**-0.11**										
12	*ROA*	**-0.26**	0.00	0.00	**0.07**	**-0.42**	**0.36**	**0.30**	**0.04**	0.01	**0.08**	**0.21**									
13	*FIRM_AGE*	**-0.06**	**0.08**	**0.08**	**0.07**	**-0.24**	**0.33**	**0.30**	**-0.14**	**-0.02**	**0.19**	**-0.18**	**0.08**								
14	*LEV*	**-0.14**	**0.02**	**0.01**	**-0.07**	**-0.09**	**0.18**	**0.17**	**-0.08**	0.00	**0.21**	**-0.08**	**-0.07**	**0.05**							
15	*CASH*	**-0.12**	**0.03**	**0.03**	**0.09**	**-0.38**	**0.35**	**0.29**	**0.06**	0.01	**0.08**	**0.19**	**0.94**	**0.09**	**-0.15**						
16	*HERFINDAHL*	**-0.09**	**-0.09**	**-0.09**	**0.15**	**0.01**	**0.01**	**0.08**	**0.02**	0.00	**-0.30**	**0.02**	**0.06**	**-0.09**	**0.05**	**0.02**					
17	*FOREIGN_SALE%*	**0.12**	**0.05**	**0.06**	**0.25**	**-0.04**	**0.20**	**0.23**	**0.02**	**-0.01**	**-0.16**	**-0.06**	**0.04**	**0.15**	**0.03**	**0.06**	**0.12**				
18	*ADR*	**0.06**	**0.07**	**0.07**	**0.18**	**-0.02**	**0.27**	**0.32**	**0.06**	**-0.02**	**-0.03**	**-0.02**	**0.03**	**0.10**	**0.05**	**0.04**	**0.09**	**0.19**			
19	*GDP*	**0.07**	**0.14**	**0.14**	0.00	**-0.03**	**0.21**	**0.06**	**-0.02**	**-0.01**	**0.18**	**-0.06**	**-0.07**	**0.25**	**-0.07**	**-0.01**	**-0.39**	0.00	**-0.04**		
20	*PERCAPITA*	**0.15**	**0.07**	**0.08**	**0.22**	**0.11**	**0.14**	**-0.03**	**0.02**	**-0.02**	**-0.20**	**-0.08**	**-0.14**	**0.10**	**-0.09**	**-0.08**	**0.01**	**0.17**	**0.02**	**0.42**	
21	*MKT_SIZE*	**0.10**	**-0.06**	**-0.04**	**0.13**	**0.15**	**-0.07**	**-0.14**	**0.07**	**-0.01**	**-0.09**	**0.04**	**-0.07**	**0.05**	**-0.12**	**-0.04**	**-0.06**	**0.05**	**-0.05**	**0.21**	**0.31**

Table 2 reports the Pearson correlation matrix. Panel A reports the correlation matrix among transparency variables. Panel B reports the correlation matrix of selected variables in main analyses. All variables are defined in Appendix A. Bold test indicates two-tailed significance at 0.01 level or below.

Table 3
Firm Transparency and Innovative Effort

Dependent Variable=*R&D* $_{t+1}$

	(1)		(2)		(3)		(4)		(5)		(6)		(7)	
	Coeff.	**t-Stat.**	**Coeff.**	**t-Stat.**	**Coeff.**	**t-Stat.**	**Coeff.**	**t-Stat.**	**Coeff.**	**t-Stat.**	**Coeff.**	**t-Stat.**	**Coeff.**	**t-Stat.**
SMOOTH_RATIO	**-0.003**	**-5.90*****												
SMOOTH_CORR			**-0.003**	**-2.55****										
ABS_ACCR					**0.000**	**-4.58*****								
INT_GAAP							**0.004**	**4.91*****						
ANALYST									**0.000**	**10.88*****				
ACCURACY											**0.000**	**2.48****		
TRANS													**0.019**	**15.11*****
FINANCE	0.007	5.62***	0.007	5.63***	0.007	5.63***	0.007	5.50***	0.007	5.17***	0.006	3.42***	0.007	5.23***
SALES	-0.002	-5.78***	-0.002	-6.00***	-0.002	-5.95***	-0.002	-6.04***	-0.002	-6.92***	-0.004	-8.37***	-0.002	-6.67***
EMPLOYMENT	0.000	0.94	0.000	1.02	0.000	0.93	0.000	0.88	0.000	-1.00	0.002	3.94***	0.000	-0.40
MTB	0.001	11.40***	0.001	11.40***	0.001	11.33***	0.001	11.35***	0.001	10.42***	0.001	9.09***	0.001	10.78***
CLOSE%	0.000	-1.52	0.000	-1.62	0.000	-1.51	0.000	-1.52	0.000	-1.52	-0.001	-2.06**	0.000	-1.58
K/L	-0.001	-6.35***	-0.001	-6.33***	-0.001	-6.42***	-0.001	-6.41***	-0.002	-7.63***	0.000	0.33	-0.001	-7.10***
SALES_GROWTH	-0.001	-2.74***	-0.001	-2.89***	-0.001	-2.84***	-0.001	-2.79***	-0.001	-2.58***	0.000	-0.07	-0.001	-2.22**
ROA	-0.285	-21.86***	-0.285	-21.88***	-0.285	-21.89***	-0.285	-21.94***	-0.283	-21.83***	-0.075	-16.22***	-0.285	-21.96***
FIRM_AGE	-0.001	-1.87*	-0.001	-1.96**	-0.001	-1.95*	-0.001	-1.82	-0.001	-2.05**	0.001	2.40**	-0.001	-1.83*
LEV	-0.003	-2.00**	-0.003	-2.06**	-0.003	-1.91*	-0.003	-2.19**	-0.001	-0.93	-0.015	-7.08***	-0.002	-1.17
CASH	0.116	18.94***	0.116	18.94***	0.116	18.95***	0.116	18.99***	0.115	18.90***	0.056	15.75***	0.116	19.00***
HERFINDAHL	0.008	2.21**	0.008	2.21**	0.008	2.20**	0.008	2.10**	0.008	2.19**	0.012	2.16**	0.008	2.01**
HERFINDAHL ^{2}	-0.012	-3.99***	-0.012	-4.00***	-0.012	-3.99***	-0.012	-3.90***	-0.012	-3.94***	-0.015	-3.47***	-0.012	-3.76***
FOREIGN_SALE%	0.009	4.07***	0.009	4.05***	0.009	4.05***	0.009	3.95***	0.009	4.03***	0.007	3.05***	0.009	3.95***
ADR	0.011	8.39***	0.011	8.43***	0.011	8.43***	0.011	8.28***	0.009	7.33***	0.011	7.99***	0.010	8.26***
GDP	-0.018	-3.51***	-0.019	-3.60***	-0.019	-3.62***	-0.020	-3.88***	-0.017	-3.23***	-0.038	-5.41***	-0.017	-3.29***
PERCAPITA	0.019	3.25***	0.019	3.30***	0.019	3.31***	0.019	3.40***	0.017	2.99***	0.040	5.32***	0.017	3.02***
MKT_SIZE	0.000	1.29	0.000	1.26	0.000	1.23	0.000	1.05	0.000	0.44	0.000	-1.29	0.000	1.20
S.E. clustering by Firm	**YES**		**YES**		**YES**		**YES**		**YES**		**YES**		**YES**	
Fixed effects	**C.I.Y.**		**C.I.Y.**		**C.I.Y.**		**C.I.Y.**		**C.I.Y.**		**C.I.Y.**		**C.I.Y.**	
Adjusted R^2	0.358		0.358		0.358		0.358		0.361		0.332		0.362	
Model *p* -value	<0.0001		<0.0001		<0.0001		<0.0001		<0.0001		<0.0001		<0.0001	
N	88687		88687		88687		88687		88687		56114		88687	

Table 3 reports the results of testing H1a on the association between transparency and *R&D*. In all regressions, Country(C), Industry (I) and Year (Y) fixed effects are included. Coefficient estimates and *p* -values are based on robust standard errors clustered at the firm-level.

***, ** and * denote significance at 1%, 5% and 10% levels (two-tailed), respectively. All variables are defined as in Appendix A.

$$R\&D_{ijt+1} = \beta_0 + \beta_1 Transparency_{ijt} + \beta_k \Sigma Controls_{ijt} + Fixed\ Effects + \varepsilon_{ijt}$$

Table 4

Transparency and the Sensitivity of Management Turnover to Innovative Output

Dependent Variable=*Pr (TURNOVER=1)* $_{t+1}$

	OUTPUT=PATENT								*OUTPUT=CITATION*							
	Baseline				Interaction				Baseline				Interaction			
	Coefficient		Marginal Effect		Coefficient		Marginal Effect		Coefficient		Marginal Effect		Coefficient		Marginal Effect	
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	Coeff.	**Z-Stat.**	**Coeff.**	**Z-Stat.**	**Coeff.**	**Z-Stat.**	**Coeff.**	**Z-Stat.**	**Coeff.**	**Z-Stat.**	**Coeff.**	**Z-Stat.**	**Coeff.**	**Z-Stat.**	**Coeff.**	**Z-Stat.**
Innovative Output																
OUTPUT	**-0.270**	**-1.76***	**-0.013**	**-1.74***	**-0.755**	**-2.46****	**-0.036**	**-2.46****	**-0.073**	**-1.69***	**-0.003**	**-1.71***	**-0.228**	**-1.90***	**-0.011**	**-1.91***
OUTPUT*HIGH_TRANS					**0.731**	**2.15****	**0.035**	**2.17****					**0.261**	**2.08****	**0.012**	**2.10****
HIGH_TRANS					0.038	0.29	0.000	-0.03					0.028	0.22	-0.001	-0.11
Standard Performance Measures																
ROA	-3.453	-3.37***	-0.165	-3.37***	-3.459	-3.38***	-0.165	-3.38***	-3.444	-3.36***	-0.164	-3.36**	-3.466	-3.37***	-0.165	-3.37***
ΔROA	-2.366	-2.02**	-0.113	-2.04**	-2.397	-2.04**	-0.114	-2.07**	-2.382	-2.03**	-0.114	-2.05**	-2.414	-2.05**	-0.115	-2.07**
RET	-0.250	-1.44	-0.012	-1.45	-0.244	-1.41	-0.012	-1.41	-0.251	-1.44	-0.012	-1.45	-0.243	-1.40	-0.012	-1.40
Other Firm- and Country-level Controls																
R&D	0.900	0.49	0.043	0.50	0.915	0.51	0.044	0.51	0.843	0.46	0.040	0.46	0.798	0.44	0.038	0.44
SIZE	0.394	5.89***	0.019	6.05***	0.394	5.88***	0.019	6.04***	0.392	5.85***	0.019	6.00***	0.391	5.83***	0.019	5.98***
MTB	0.034	1.75*	0.002	1.76*	0.033	1.71*	0.002	1.72*	0.035	1.76**	0.002	1.77*	0.033	1.70*	0.002	1.71*
CLOSE%	-0.347	-1.13	-0.017	-1.13	-0.335	-1.09	-0.016	-1.10	-0.348	-1.14	-0.017	-1.14	-0.341	-1.12	-0.016	-1.12
K/L	-0.093	-1.52	-0.004	-1.54	-0.095	-1.54	-0.005	-1.56	-0.093	-1.51	-0.004	-1.53	-0.096	-1.55	-0.005	-1.57
SALES_GROWTH	-0.683	-2.18**	-0.033	-2.19**	-0.669	-2.14**	-0.032	-2.15**	-0.687	-2.19**	-0.033	-2.20**	-0.673	-2.15**	-0.032	-2.16**
FIRM_AGE	-0.068	-0.83	-0.003	-0.83	-0.064	-0.78	-0.003	-0.79	-0.069	-0.83	-0.003	-0.84	-0.065	-0.79	-0.003	-0.79
LEV	0.336	0.79	0.016	0.80	0.360	0.85	0.017	0.85	0.343	0.81	0.016	0.81	0.371	0.87	0.018	0.88
GDP	-1.781	-0.66	-0.085	-0.67	-1.701	-0.62	-0.081	-0.62	-1.722	-0.64	-0.082	-0.64	-1.673	-0.60	-0.080	-0.61
PERCAPITA	0.560	0.19	0.027	0.20	0.467	0.16	0.022	0.16	0.498	0.17	0.024	0.17	0.442	0.15	0.021	0.15
MKT_SIZE	0.003	1.78*	0.000	1.80*	0.003	1.84*	0.000	1.86*	0.003	1.79**	0.000	1.81*	0.003	1.86*	0.000	1.88*
S.E. clustering by Firm	**YES**				**YES**				**YES**				**YES**			
Fixed effects	**C.I.Y.**				**C.I.Y.**				**C.I.Y.**				**C.I.Y.**			
Adjusted R^2	0.212				0.214				0.211				0.213			
Model *p*-value	<0.0001				<0.0001				<0.0001				<0.0001			
N	10256				10256				10256				10256			

Table 4 reports the logit regression results of testing H1b on the sensitivity of management turnover (*TURNOVER*) to innovative output (*PATENT* or *CITATION*) conditional on the level of transparency (*HIGH_TRANS*). Marginal effects are calculated as the change in the probability of a forced turnover for a one unit change in the explanatory variable, holding all other variables at the mean values. Z--statistics are calculated using the delta method (Ai and Norton, 2008). In all regressions, Country(C), Industry (I) and Year (Y) fixed effects are included. Coefficient estimates and *p*-values are based on robust standard errors clustered at the firm-level.

***, ** and * denote significance at 1%, 5% and 10% levels (two-tailed), respectively. All variables are defined in Appendix A.

$Pr\ (Turnover=1)_{ijt+1} = \beta_0 + \beta_1 Output_{ijt} + \beta_2\ High\_Trans_{ijt} + \beta_3\ Output_{ijt} * High\_Trans_{ijt} + \beta_k\ \Sigma Controls_{ijt} + Fixed\ Effects + \varepsilon_{ijt}$

Table 5
Cross-sectional Results of Transparency and Innovative Effort
Conditional on Ex-ante Career Risk (Dependent Variable=$R\&D_{t+1}$)

	Insider Ownership				Product Development Cycle			
	(1) HIGH		(2) LOW		(3) LONG		(4) SHORT	
	Coeff.	t-Stat.	Coeff.	t-Stat.	Coeff.	t-Stat.	Coeff.	t-Stat.
TRANS	**0.013**	**9.21*****	**0.023**	**11.50*****	**0.020**	**10.54*****	**0.012**	**7.33*****
LEFT-RIGHT (*p*-value)	F=20.18 (p<0.01)				F=8.46 (p<0.01)			
Controls	YES		YES		YES		YES	
S.E. clustering by Firm	YES		YES		YES		YES	
Fixed effects	C.I.Y.		C.I.Y.		C.I.Y.		C.I.Y.	
Adjusted R^2	0.292		0.417		0.348		0.417	
Model *p*-value	<0.0001		<0.0001		<0.0001		<0.0001	
N	44267		44420		51554		37133	

Table 5 reports the results of testing H1c on cross-sectional variation of transparency–R&D relation conditional on ex-ante career risk. Regressions are run separately for two subgroups based on the median cutoff of *INSIDE_OWN%* and *CYCLE*, respectively. In all regressions, Country(C), Industry (I) and Year (Y) fixed effects are included. Coefficient estimates and *p*-values are based on robust standard errors clustered at the firm-level.

***, ** and * denote significance at 1%, 5% and 10% levels (two-tailed), respectively. All variables are defined as in Appendix A.

$R\&D_{ijt+1} = \beta_0 + \beta_1 Transparency_{ijt} + \beta_k \Sigma Controls_{ijt} + Fixed\ Effects + \varepsilon_{ijt}$

Table 6
Firm Transparency and Innovative Efficiency

	$PATENT_{t+1}$ (1)		$PATENT_{t+1}$ (2)		$PATENT_{t+1}$ (3)		$PATENT_{t+1}$ (4)		$PATENT_{t+1}$ (5)		$PATENT_{t+1}$ (6)		$PATENT_{t+1}$ (7)		IE_PATENT_{t+1} (8)	
	Coeff.	**t-Stat.**	**Coeff.**	**t-Stat.**	**Coeff.**	**t-Stat.**	**Coeff.**	**t-Stat.**	**Coeff.**	**t-Stat.**	**Coeff.**	**t-Stat.**	**Coeff.**	**t-Stat.**	**Coeff.**	**t-Stat.**
SMOOTH_RATIO	**-0.017**	**-1.77***														
SMOOTH_CORR			**-0.033**	**-1.83***												
ABS_ACCR					**0.000**	**-1.79***										
INT_GAAP							**0.075**	**3.82*****								
ANALYST									**0.003**	**2.93*****						
ACCURACY											**0.004**	**1.86***				
TRANS													**0.138**	**5.86*****	**0.475**	**5.72*****
R&D	1.027	10.33***	1.029	10.34***	0.883	8.57***	0.859	8.24***	0.856	8.21***	1.031	7.24***	0.829	8.03***		
FINANCE	0.027	5.04***	0.027	5.04***	0.025	4.65***	0.023	4.30***	0.022	4.11***	0.049	4.16***	0.022	4.08***	0.109	3.94***
SALES	-0.012	-4.41***	-0.012	-4.49***	-0.008	-2.92***	-0.008	-3.00***	-0.010	-3.50***	-0.013	-2.66***	-0.009	-3.37***	-0.019	-1.35
EMPLOYMENT	0.030	8.57***	0.030	8.56***	0.026	7.72***	0.025	7.49***	0.023	6.47***	0.029	5.63***	0.023	6.96***	0.067	4.12***
MTB	0.000	0.23	0.000	0.24	0.001	0.99	0.001	0.99	0.000	0.25	0.001	1.32	0.000	0.42	0.006	1.87*
CLOSE%	0.000	-1.32	0.000	-1.76*	0.000	-0.08	0.000	-0.12	0.000	0.21	0.017	0.90	0.000	0.14	0.109	1.94*
K/L	0.006	2.83***	0.006	2.86***	0.007	3.72***	0.007	3.67***	0.006	2.84***	0.008	2.57**	0.006	3.16***	0.037	3.26***
SALES_GROWTH	0.005	1.14	0.004	1.06	0.004	0.93	0.005	1.10	0.005	1.12	0.001	0.20	0.006	1.54	0.024	1.11
ROA	0.007	0.12	0.007	0.12	0.010	0.18	-0.007	-0.12	0.008	0.14	0.041	0.39	-0.011	-0.20	-0.405	-2.32**
FIRM_AGE	0.013	2.22**	0.013	2.18**	0.013	2.09**	0.014	2.21**	0.013	2.06**	0.023	3.71***	0.013	2.13**	0.039	1.68*
LEV	-0.018	-0.89	-0.019	-0.92	-0.022	-1.06	-0.027	-1.29	-0.012	-0.57	-0.026	-0.75	-0.013	-0.60	0.079	0.95
CASH	0.025	0.93	0.024	0.90	0.015	0.60	0.021	0.82	0.016	0.62	0.025	0.51	0.023	0.89	0.213	2.66***
HERFINDAHL	-0.018	-0.28	-0.018	-0.28	-0.009	-0.13	-0.022	-0.30	-0.008	-0.12	0.010	0.09	-0.016	-0.22	0.147	0.63
$HERFINDAHL^2$	0.009	0.16	0.008	0.16	0.002	0.04	0.011	0.20	0.002	0.03	-0.015	-0.18	0.008	0.15	-0.147	-0.78
FOREIGN_SALE%	0.047	2.45**	0.047	2.45**	0.033	1.99**	0.027	1.66*	0.031	1.89*	0.025	1.42	0.029	1.79*	0.111	2.23**
ADR	0.052	1.83*	0.052	1.85*	0.054	1.94*	0.050	1.81*	0.046	1.64	0.052	1.66*	0.053	1.89*	0.126	1.66*
GDP	0.884	9.76***	0.885	9.76***	0.868	9.71***	0.851	9.76***	0.886	9.85***	0.983	8.99***	0.891	9.87***	1.224	9.08***
PERCAPITA	-0.661	-8.51***	-0.662	-8.52***	-0.651	-8.45***	-0.661	-8.57***	-0.668	-8.64***	-0.751	-7.89***	-0.676	-8.71***	-0.690	-4.81***
MKT_SIZE	0.000	4.27***	0.000	4.29***	0.000	3.99***	0.000	4.16***	0.000	3.61***	0.000	2.93***	0.000	4.12***	0.000	1.49
S.E. clustering by Firm	YES		YES		YES		YES		YES		YES		YES		YES	
Fixed effects	C.I.Y.		C.I.Y.		C.I.Y.		C.I.Y.		C.I.Y.		C.I.Y.		C.I.Y.		C.I.Y.	
Adjusted R^2	0.102		0.102		0.114		0.116		0.115		0.130		0.116		0.123	
Model *p*-value	<0.0001		<0.0001		<0.0001		<0.0001		<0.0001		<0.0001		<0.0001		<0.0001	
N	88687		88687		88687		88687		88687		56114		88687		50738	

Table 6 reports the results of testing H2a on the association between transparency and innovative efficiency. Column (1)-(7), and (8) report the results using *PATENT* (after controlling for R&D) and *IE_PATENT* as the dependent variable, respectively. The sample size in column (8) is reduced to 50,738 firm-years due to the missing values in calculating *IE_PATENT*. In all regressions, country(C), industry (I) and year (Y) fixed effects are included. Coefficient estimates and *p*-values are based on robust standard errors clustered at the firm-level.

***, ** and * denote significance at 1%, 5% and 10% levels (two-tailed), respectively. All variables are defined as in Appendix A.

$Outcome_{ijt+1} = \beta_0 + \beta_1 Transparency_{ijt} + \beta_k \Sigma Controls_{ijt} + Fixed\ Effects + \varepsilon_{ijt}$

Table 7

Transparency and the Sensitivity of R&D to Investment Opportunity Set

Dependent Variable=*R&D* $_{t+1}$

	(1)		(2)	
	Coeff.	**t-Stat.**	**Coeff.**	**t-Stat.**
Q	**0.008**	**14.15*****	**0.006**	**9.30*****
Q*HIGH_TRANS			**0.003**	**4.09*****
HIGH_TRANS			0.000	-0.44
FINANCE	0.005	3.58***	0.005	3.62***
SALES	-0.002	-5.64***	-0.002	-6.09***
EMPLOYMENT	0.001	1.68*	0.000	1.18
MTB	0.000	-0.47	0.000	-0.41
CLOSE%	0.000	-0.97	0.000	-1.02
K/L	-0.001	-4.37***	-0.001	-4.79***
SALES_GROWTH	-0.002	-3.72***	-0.002	-3.20***
ROA	-0.300	-19.61***	-0.300	-19.69***
FIRM_AGE	0.000	0.19	0.000	0.00
LEV	0.000	-0.25	0.000	0.12
CASH	0.121	16.83***	0.121	16.84***
HERFINDAHL	0.010	2.72***	0.010	2.61***
$HERFINDAHL^2$	-0.014	-4.25***	-0.013	-4.12***
FOREIGN_SALE%	0.007	3.36***	0.007	3.28***
ADR	0.008	6.74***	0.008	6.65***
GDP	-0.028	-5.03***	-0.027	-4.82***
PERCAPITA	0.028	4.62***	0.027	4.44***
MKT_SIZE	0.000	1.11	0.000	1.17
S.E. clustering by Firm	YES		YES	
Fixed effects	C.I.Y.		C.I.Y.	
Adjusted R^2	0.371		0.376	
Model *p* -value	<0.0001		<0.0001	
N	88687		88687	

Table 7 reports the results of testing H2b on the sensitivity of R&D investment (R&D) to the investment opportunity set (*Q*) conditional on the level of transparency. In all regressions, Country(C), Industry (I) and Year (Y) fixed effects are included. Coefficient estimates and *p* -values are based on robust standard errors clustered at the firm-level.

***, ** and * denote significance at 1%, 5% and 10% levels (two-tailed), respectively. All variables are defined in Appendix A.

$R\&D_{ijt+1} = \beta_0 + \beta_1 Q_{ijt} + \beta_2 High\_trans_{ijt} + \beta_3 Q_{ijt} * High\_trans_{ijt} + \beta_k \Sigma Controls_{ijt} + Fixed\ Effects + \varepsilon_{ijt}$

Table 8

Cross-sectional Results of Transparency and Innovative Efficiency

Panel A: Conditional on Monitoring Demand (Dep. Var.=*IE_PATENT*$_{t+1}$)

	Organizational Complexity				Rule of Law			
	(1) HIGH		(2) LOW		(3) HIGH		(4) LOW	
	Coeff.	t-Stat.	Coeff.	t-Stat.	Coeff.	t-Stat.	Coeff.	t-Stat.
TRANS	**0.590**	**5.84*****	**0.059**	**0.49**	**0.003**	**0.04**	**0.576**	**4.19*****
LEFT-RIGHT (*p*-value)	F=11.35 (p<0.01)				F=13.59 (p<0.01)			
Controls	YES		YES		YES		YES	
S.E. clustering by Firm	YES		YES		YES		YES	
Fixed effects	C.I.Y.		C.I.Y.		C.I.Y.		C.I.Y.	
Adjusted R^2	0.128		0.106		0.061		0.131	
Model *p*-value	<0.0001		<0.0001		<0.0001		<0.0001	
N	29966		20772		25522		25216	

Panel B: Conditional on Proprietary Cost (Dep. Var.=*IE_PATENT*$_{t+1}$)

	Property Rights Protection				Contract Enforceability			
	(1) STRONG		(2) WEAK		(3) STRONG		(4) WEAK	
	Coeff.	t-Stat.	Coeff.	t-Stat.	Coeff.	t-Stat.	Coeff.	t-Stat.
TRANS	**0.687**	**5.47*****	**-0.085**	**-0.940**	**0.528**	**4.82*****	**-0.051**	**-0.51**
STRONG-WEAK (*p*-value)	F=30.65 (p<0.01)				F=15.53 (p<0.01)			
Controls	YES		YES		YES		YES	
S.E. clustering by Firm	YES		YES		YES		YES	
Fixed effects	C.I.Y.		C.I.Y.		C.I.Y.		C.I.Y.	
Adjusted R^2	0.144		0.077		0.136		0.073	
Model *p*-value	<0.0001		<0.0001		<0.0001		<0.0001	
N	28101		22637		36949		13789	

Table 8, panel A and B reports the results of testing H2c and H2d on cross-sectional variation of transparency–innovative efficiency relation conditional on monitoring demand and proprietary cost. In Panel A, regressions are run separately for two subgroups based on the median cutoff of *COMPLEXITY* and *RULE_LAW*, respectively. In Panel B, regressions are run separately for two subgroups based on the median cutoff of *PROPERTY_RIGHTS* and *ENFORCE*, respectively. In all regressions, Country(C), Industry (I) and Year (Y) fixed effects are included. Coefficient estimates and *p*-values are based on robust standard errors clustered at the firm-level.

***, ** and * denote significance at 1%, 5% and 10% levels (two-tailed), respectively. All variables are defined as in Appendix A.

$IE\_PATENT_{ijt+1} = \beta_0 + \beta_1 Transparency_{ijt} + \beta_k \Sigma Controls_{ijt} + Fixed\ Effects + \varepsilon_{ijt}$

Table 9
Single-country Analysis using only the U.S. Firms

	Innovation Effort				Innovative Efficiency							
	R&D $_{t+1}$				***IE_PATENT*** $_{t+1}$				***IE_CITATION*** $_{t+1}$			
	(1)		**(2)**		**(3)**		**(4)**		**(5)**		**(6)**	
	Coeff.	**t-Stat.**	**Coeff.**	**t-Stat.**	**Coeff.**	**t-Stat.**	**Coeff.**	**t-Stat.**	**Coeff.**	**t-Stat.**	**Coeff.**	**t-Stat.**
TRANS	**0.024**	**5.50*****	**0.002**	**1.89***	**0.146**	**3.26*****	**0.060**	**2.54****	**0.232**	**3.13*****	**0.107**	**2.69*****
FINANCE	0.025	10.57***	-0.004	-4.87***	0.006	0.88	0.006	0.93	0.020	1.60	0.011	1.10
SALES	-0.007	-4.95***	-0.012	-19.24***	-0.011	-1.57	-0.004	-0.94	-0.021	-1.86*	-0.008	-0.99
EMPLOYMENT	-0.001	-1.03	0.008	10.68***	0.029	3.06***	0.018	2.95***	0.041	2.83***	0.022	2.15**
MTB	0.000	2.06**	0.000	-6.82***	0.000	-0.53	0.000	0.80	-0.001	-0.64	0.000	0.70
CLOSE%	-0.033	-9.60***	-0.003	-1.31	-0.073	-2.12**	-0.013	-0.76	-0.151	-2.88***	-0.021	-0.73
K/L	-0.002	-1.98**	0.001	1.10	0.016	1.92*	0.016	3.33***	0.029	2.30**	0.026	3.13***
SALES_GROWTH	-0.017	-10.59***	-0.001	-0.76	0.009	0.98	-0.001	-0.09	0.008	0.58	-0.001	-0.08
ROA	-0.128	-16.76***	-0.043	-23.62***	-0.006	-0.35	0.006	0.42	-0.014	-0.52	0.018	0.77
FIRM_AGE	0.000	0.02	0.003	3.17***	0.013	1.27	-0.024	-2.71***	0.027	1.74*	-0.004	-0.26
LEV	-0.004	-0.83	0.001	1.14	0.004	0.34	0.007	0.67	-0.003	-0.15	0.003	0.15
CASH	0.034	11.50***	0.007	9.97***	0.000	0.00	-0.001	-0.27	0.005	0.72	-0.004	-0.49
HERFINDAHL	-0.224	-15.45***	-0.007	-0.59	0.147	0.70	0.190	1.45	0.343	1.15	0.267	1.21
HERFINDAHL ^{2}	0.217	14.33***	0.002	0.17	-0.278	-1.11	-0.152	-1.15	-0.476	-1.39	-0.174	-0.78
FOREIGN_SALE%	0.025	6.97***	-0.003	-1.56	-0.033	-0.68	-0.012	-0.63	-0.051	-0.70	-0.054	-1.77*
GDP	-1.104	-2.60***	-0.028	-0.07	-9.598	-2.87***	-3.282	-0.31	-19.756	-3.96***	-13.351	-0.74
PERCAPITA	1.286	2.88***	0.124	0.31	11.281	2.75***	3.477	0.27	23.215	3.80***	15.216	0.70
MKT_SIZE	0.000	-2.29**	0.000	0.16	0.000	2.12**	0.000	1.00	0.000	1.31	0.000	0.62
S.E. clustering by Firm	**YES**		**YES**		**YES**		**YES**		**YES**		**YES**	
Fixed Effects	**I.Y.**		**F.Y.**		**I.Y.**		**F.Y.**		**I.Y.**		**F.Y.**	
Adjusted R^2	0.328		0.786		0.670		0.670		0.635		0.635	
Model *p* -value	<0.0001		<0.0001		<0.0001		<0.0001		<0.0001		<0.0001	
N	64715		64715		41707		41707		41707		41707	

Table 9 reports the results of single-country analysis using the U.S. sample. In column (1)/ (3)/ (5), Industry (I) and Year (Y) fixed effects are controlled. In column (2)/(4)/(6), Firm (F) and Year (Y) fixed effects are included. In all regressions, coefficient estimates and *p* -values are based on robust standard errors clustered at the firm-level.

***, ** and * denote significance at 1%, 5% and 10% levels (two-tailed), respectively. All variables are defined as in Appendix A.

$Innovation_{iit+1} = \beta_0 + \beta_1 Transparency_{iit} + \beta_k \Sigma Controls_{iit} + Fixed\ Effects + \varepsilon_{iit}$

Table 10

Difference-in-Differences Regression Results of the Effect of Mandatory IFRS Adoption on Innovation

	Innovation Effort						**Innovative Efficiency**											
	R&D$_t$						***IE_PATENT$_t$***						***IE_CITATION$_t$***					
	(1)		**(2)**		**(3)**		**(4)**		**(5)**		**(6)**		**(7)**		**(8)**		**(9)**	
	[t-1, t+3]		***[t-3, t+3]***		***[t-5, t+5]***		***[t-1, t+3]***		***[t-3, t+3]***		***[t-5, t+5]***		***[t-1, t+3]***		***[t-3, t+3]***		***[t-5, t+5]***	
	Coeff.	**t-Stat.**	**Coeff.**	**t-Stat.**	**Coeff.**	**t-Stat.**	**Coeff.**	**t-Stat.**	**Coeff.**	**t-Stat.**	**Coeff.**	**t-Stat.**	**Coeff.**	**t-Stat.**	**Coeff.**	**t-Stat.**	**Coeff.**	**t-Stat.**
IFRS	-0.008	-1.31	-0.014	-0.89	-0.014	-1.14	-1.125	-5.96***	-1.381	-7.76***	-0.671	-3.04***	-1.557	-5.60***	-1.713	-6.75***	-0.545	-1.71*
POST	-0.002	-2.29**	-0.002	-3.20***	-0.002	-2.29**	-0.104	-3.79***	-0.081	-3.04***	-0.209	-4.59***	-0.150	-3.68***	-0.124	-3.12***	-0.321	-4.51***
POST*IFRS	**0.002**	**2.27****	**0.003**	**2.91*****	**0.002**	**2.33****	**0.100**	**4.07*****	**0.100**	**4.91*****	**0.269**	**6.67*****	**0.131**	**3.51*****	**0.118**	**3.90*****	**0.319**	**5.30*****
FINANCE	0.012	4.51***	0.012	4.97***	0.012	5.62***	0.098	4.13***	0.085	3.95***	0.186	5.38***	0.148	3.92***	0.126	3.72***	0.276	4.91***
SALES	-0.003	-5.77***	-0.003	-5.18***	-0.003	-6.02***	-0.035	-3.62***	-0.033	-3.45***	-0.010	-0.58	-0.051	-3.53***	-0.048	-3.30***	-0.017	-0.64
EMPLOYMENT	0.000	0.73	0.000	0.41	0.000	0.33	0.120	10.26***	0.117	10.02***	0.117	6.08***	0.174	9.98***	0.166	9.70***	0.174	5.90***
MTB	0.001	6.61***	0.001	6.84***	0.001	8.59***	-0.001	-0.44	0.001	0.22	0.002	0.59	0.000	0.13	0.003	0.78	0.006	1.01
CLOSE%	-0.011	-5.77***	-0.011	-6.38***	-0.011	-7.06***	-0.027	-0.59	-0.058	-1.32	0.057	0.79	-0.042	-0.63	-0.091	-1.41	0.084	0.78
K/L	0.000	-0.47	0.000	-0.36	0.000	-0.39	0.028	3.54***	0.027	3.37***	0.023	1.39	0.042	3.60***	0.040	3.48***	0.038	1.53
SALES_GROWTH	-0.003	-2.28**	-0.002	-2.59***	-0.001	-1.72*	0.067	3.49***	0.061	3.73***	0.082	2.64***	0.095	3.29***	0.087	3.58***	0.124	2.63***
ROA	-0.348	-14.29***	-0.329	-15.00***	-0.305	-16.13***	-0.691	-3.86***	-0.776	-4.48***	-0.817	-3.40***	-1.254	-4.60***	-1.327	-5.22***	-1.441	-4.05***
FIRM_AGE	-0.001	-1.20	-0.001	-1.88*	-0.001	-1.97**	0.015	1.02	0.027	1.89*	0.015	0.60	0.018	0.85	0.036	1.71	0.021	0.57
LEV	-0.005	-1.93*	-0.006	-2.65***	-0.006	-2.97***	-0.012	-0.19	-0.024	-0.39	0.060	0.59	-0.052	-0.59	-0.079	-0.91	0.011	0.07
CASH	0.144	12.11***	0.132	12.71***	0.120	13.40***	0.305	3.55***	0.309	3.83***	0.347	3.11***	0.559	4.35***	0.533	4.54***	0.614	3.74***
HERFINDAHL	0.000	-0.02	-0.002	-0.37	0.000	0.04	-0.262	-1.39	-0.216	-1.15	-0.233	-0.87	-0.374	-1.39	-0.285	-1.07	-0.319	-0.82
HERFINDAHL^2	-0.008	-1.62	-0.005	-1.24	-0.007	-1.83	0.240	1.58	0.197	1.30	0.141	0.63	0.337	1.54	0.255	1.18	0.170	0.51
FOREIGN_SALE%	0.015	7.67***	0.013	6.00***	0.011	4.79***	0.167	3.62***	0.106	2.19**	0.145	2.32**	0.268	3.88***	0.178	2.47**	0.236	2.47**
ADR	0.009	4.27***	0.010	4.88***	0.010	5.37***	0.154	1.79*	0.163	1.94*	0.145	1.49	0.227	1.85*	0.247	2.08**	0.234	1.64
GDP	0.010	0.94	-0.001	-0.11	-0.003	-0.57	0.716	3.75***	0.556	3.92***	1.116	5.38***	1.056	3.79***	0.716	3.67***	1.548	5.27***
PERCAPITA	-0.013	-1.10	-0.004	-0.72	-0.001	-0.11	-0.199	-0.95	0.047	0.32	-0.831	-3.59***	-0.342	-1.12	0.036	0.18	-1.315	-3.99***
MKT_SIZE	0.000	-1.26	0.000	-2.63***	0.000	-1.69*	0.001	4.46***	0.000	2.37**	0.000	-0.09	0.001	4.42***	0.000	2.46**	0.000	0.57
S.E. clustering by Country	**YES**		**YES**		**YES**		**YES**		**YES**		**YES**		**YES**		**YES**		**YES**	
Fixed effects	**C.I.Y.**		**C.I.Y.**		**C.I.Y.**		**C.I.Y.**		**C.I.Y.**		**C.I.Y.**		**C.I.Y.**		**C.I.Y.**		**C.I.Y.**	
Adjusted R^2	0.133		0.138		0.143		0.133		0.138		0.143		0.135		0.133		0.146	
Model *p*-value	<0.0001		<0.0001		<0.0001		<0.0001		<0.0001		<0.0001		<0.0001		<0.0001		<0.0001	
N	14748		20247		30856		14748		20247		30856		14748		20247		30856	

Table 10 reports the Difference-in-Differences results of the effect of mandatory IFRS adoption on innovation. Column (1)-(3) report the results for *R&D*, column (4)-(6), (7)-(9) report the results for *IE_PATENT* and *IE_CITATION*. For each dependent variable, the results are reported based on three event windows: [t-1,t+3], [t-3,t+3] and [t-5,t+5]. In all regressions, Country(C), industry (I) and Year (Y) fixed effects are included. Coefficient estimates and *p*-values are based on robust standard errors clustered at the country-level.

***, ** and * denote significance at 1%, 5% and 10% levels (two-tailed), respectively. All variables are defined in Appendix A.

$Innovation_{ijt} = \beta_0 + \beta_1 POST_{ijt} + \beta_2 IFRS_{ijt} + \beta_3 POST_{ijt} * IFRS_{ijt} + \beta_4 Controls_{ijt} + Fixed\ Effects + \varepsilon_{ijt}$

Table 11

Dynamic Analysis of Change in Transparency on Change in Innovation

	Innovative Effort				**Innovative Efficiency**							
	Change Analysis $\Delta R\&D_{t+1}$ **(1)**		***Dynamic Analysis*** $\Delta R\&D_{t}$ **(2)**		***Change Analysis*** ΔIE_PATENT_{t+1} **(3)**		***Dynamic Analysis*** ΔIE_PATENT_{t} **(4)**		***Change Analysis*** $\Delta IE\_CITATION_{t+1}$ **(5)**		***Dynamic Analysis*** $\Delta IE\_CITATION_{t}$ **(6)**	
	Coeff.	**t-Stat.**	**Coeff.**	**t-Stat.**	**Coeff.**	**t-Stat.**	**Coeff.**	**t-Stat.**	**Coeff.**	**t-Stat.**	**Coeff.**	**t-Stat.**
$\Delta TRANS_{t-3}$			**0.001**	**1.15**			**0.270**	**2.68***			**0.424**	**2.65***
$\Delta TRANS_{t-2}$			**0.002**	**2.68***			**0.229**	**1.83***			**0.262**	**1.96***
$\Delta TRANS_{t-1}$			**0.002**	**2.19****			**0.187**	**2.01****			**0.276**	**2.25****
$\Delta TRANS_{t}$	**0.001**	**2.77*****	**0.003**	**2.70*****	**0.118**	**2.70*****	**0.098**	**0.93**	**0.158**	**2.54****	**0.181**	**1.07**
$\Delta TRANS_{t+1}$			0.001	1.16			0.061	0.61			0.045	0.27
$\Delta TRANS_{t+2}$			0.001	0.48			0.079	0.74			0.163	0.95
$\Delta TRANS_{t+3}$			0.000	0.44			0.090	1.02			0.182	1.04
ΔControls	**YES**		**YES**		**YES**		**YES**		**YES**		**YES**	
S.E. clustering by Firm	**YES**		**YES**		**YES**		**YES**		**YES**		**YES**	
Fixed Effects	**C. I. Y**		**C. I. Y**		**C. I. Y**		**C. I. Y**		**C. I. Y**		**C. I. Y**	
Adjusted R^2	0.020		0.114		0.022		0.203		0.021		0.204	
Model *p* -value	<0.0001		<0.0001		<0.0001		<0.0001		<0.0001		<0.0001	
N	68996		27878		48890		11439		48890		11439	

Table 11 reports the results of dynamic analysis examining the effects of changes in transparency on changes in innovation. Column (1)/(2), (3)/(4) and (5)/(6) report the results when $\Delta R\&D$, ΔIE_PATENT, and $\Delta IE\_CITATION$ are used as the dependent variables, respectively. For each dependent variable, I report the results under two different specifications: (1) a traditional change model examining the effect of change in transparency in year t on subsequent change in innovation in year t+1 , and (2) a dynamic analysis examining the effects of three-year lead and lag changes in transparency on change in innovation in year t. $\Delta TRANS_{t+n}$ ($\Delta TRANS_{t-n}$) is the n[th] lead (lag) value of $\Delta TRANS$. All control variables are included but not reported for brevity. In all regressions, Country(C), industry (I) and Year (Y) fixed effects are included. Coefficient estimates and *p* -values are reported based on robust standard errors clustered at the firm-level.

***, ** and * denote significance at 1%, 5% and 10% levels (two-tailed), respectively. All variables are defined as in Appendix A.

$$\Delta Innovation_{ijt+1} = \beta_0 + \beta_1 \Delta Transparency_{ijt} + \beta_k \Sigma \Delta Controls_{ijt} + Fixed\ Effects + \varepsilon_{ijt}$$