Does audit quality enhance or impede firm innovation?

Lily H.G. Nguyen, Le Vu and Xiangkang Yin*

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JEL classification: G34; M42; O31

Keywords: Audit quality; Innovation; Patent

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* Lily H.G. Nguyen, La Trobe University; Le Vu, La Trobe University; Xiangkang Yin, corresponding author, Department of Economics and Finance, La Trobe Business School, La Trobe University, Victoria 3086, Australia, Email: x.yin@latrobe.edu.au. We thank Balasingham Balachandran and seminar participants at La Trobe University for many constructive comments and suggestions. Le Vu gratefully acknowledges financial supports from Prime Minister's Australia Asia Incoming Postgraduate Scholarship (Endeavour Award) and La Trobe University's David Myers Scholarship.

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1. Introduction

Technological breakthroughs and innovations are the key drivers of a country's long-term economic growth (Romer, 1987, 1990; Solow, 1957). Given the major contributions that innovation makes to the economy, researchers have recently focused on how firm- and country-level characteristics affect innovation (e.g., Ang, 2014; Cho et al., 2016; Hsu et al., 2014). Although auditing is valued for its ability to provide greater independent assurance of the credibility of accounting information, and thus, improves resource allocation and contracting efficiency (DeFond and Zhang, 2014), there is currently scant evidence on the effect of audit quality on firm innovation in the existing literature. We fill this gap by examining whether the audit quality of a firm enhances or impedes its innovation.

Why is this issue so important? Anecdotal evidence suggests that audit quality is related to firm innovation. The case of Catapult Communications, a telecom test equipment producer, is an illustrative example. After switching from Deloitte & Touche (a Big 4 auditor) to Stonefield Josephson (a non-Big 4 auditor) in 2008, Catapult Communications applied for a patent the following year to protect its new product, the User Equipment Simulation test system, which is capable of simulating thousands of user equipment performing voices, videos, and data calls over the Common Public Radio Interface.[1] As a result, Catapult Communications' sales revenue for the first quarter of 2009 increased by 22% to $12.1 million from $9.9 million for the same period of 2008. Since then, this new product has become an inspiration for later innovations in long-term evolution access network (Akman et al., 2012; Asokan and Sundhar, 2015; Balkwill, 2015; Devarasetty et al., 2016; Subramanian et al., 2015). The Catapult Communications case apparently

[1] For more details, see http://www.marketwired.com/press-release/catapult-communications-announces-high-capacity-lte-ue-simulation-test-system-nasdaq-catt-1244663.htm.

supports the argument that switching from a Big 4 auditor to a non-Big 4 auditor, i.e., a reduction in audit quality, leads to a boost in firm innovation.

Why does audit quality matter? Our first hypothesis, which dovetails with the Catapult Communications example, argues that audit quality adversely affects firm innovation. This view is rooted in a pervasive and well-documented phenomenon of managerial myopia in which managers tend to sacrifice long-term, value-enhancing innovative projects for short-term earnings goals due to conflicts of interest between management and shareholders or managers' career concerns (e.g., Graham et al., 2005; Porter and Wayland, 1992; Stein, 1988). This myopic behavior can become even worse in firms with high audit quality for several reasons. First, these firms may attract more financial analysts, who rely heavily on firms' financial reports to formulate their forecasts on the firms (Lang and Lundholm, 1996). Since financial analysts often pressurize managers to meet short-term earnings targets, greater financial analyst coverage impedes the firms' investment in long-term innovative projects (He and Tian, 2013). Second, the high quality of a firm's audit may also attract more short-term investors, such as non-dedicated institutional investors whose trades are frequently based on current earnings rather than on long-term fundamental value. Such institutions often place excessive pressure on managers to meet short-term earnings targets, leading them to sacrifice research and development (R&D) investments (Bushee, 1998, 2001). Moreover, high audit quality also increases a firm's visibility, making it a more likely target for mergers and acquisitions (Yuan et al., 2013). Under threat of a takeover, a firm's manager is likely to have weaker incentives to invest in long-term innovative projects (Atanassov, 2013).

This story is not one-sided, though. Audit quality can contribute positively to firm innovation. First, if high audit quality serves as a monitoring device (Watts and Zimmerman, 1983), then it can mitigate the managers' myopic behavior concerning their focus on short-term earnings targets rather than on long-term investments in innovation projects. Second, the credibility of financial reports increases in the firms with high audit quality (e.g., Becker et al., 1998; DeFond and Zhang, 2014), which in turn alleviates informational asymmetry between firms and uninformed capital suppliers (Abdel-Khalik and Solomon, 1988). As a result, such firms not only can borrow at a lower cost for debt (Mansi et al., 2004) but also can increase their debt levels and become more responsive to their investment opportunities (Kausar et al., 2016). Further, they can raise equity more frequently and make larger equity issues (Chang et al., 2009). Accordingly, firms with high audit quality should have a lower cost of capital or better access to financing sources, which allows them to better finance their value-enhancing innovative projects. In addition, firms with better financial reporting quality, which probably arises from their use of high-quality audit services, improve their investment efficiency (e.g., Biddle and Hilary, 2006; Biddle et al., 2009), which may eventually lead to higher innovation outputs. Therefore, in our second hypothesis, we argue that high audit quality improves firm innovation.

We test these competing hypotheses using a sample of 7,482 U.S. firms for a period from 2000 to 2009. As in the auditing literature (e.g., Behn et al., 2008; Chang et al., 2009; Francis et al., 2014), we use a dummy variable indicating whether a firm chooses a Big 4 auditor in a given fiscal year for its auditing service as our main measure of audit quality. Although it remains challenging to find the best proxy for audit quality (DeFond and Zhang, 2014), auditor choice has been commonly used as a proper measure of audit quality in the literature (DeFond et al., 2016). To ensure that our findings are robust, we also use audit fees, industry specialists, and going-concern opinions as alternative proxies for audit quality. Following the innovation literature (e.g., Kogan et al., 2016), we use firm-level patent counts and patent citations as our measures of firm innovation.

Our baseline results show a negative relationship between audit quality and firm innovation. In terms of economic significance, firms with a Big 4 auditor have 13.9% fewer patent counts and 13.6% fewer patent citations than firms with a non-Big 4 auditor. Moreover, if a firm downgrades its audit quality, i.e., switching from a Big 4 auditor to a non-Big 4 auditor, it leads to an increase in innovation output. These results support our first hypothesis that audit quality adversely affects firm innovation.

Although we find a negative effect of audit quality on firm innovation, a major concern is that this relationship could be endogenously determined. Would this negative relationship be entirely driven by some unobservable characteristics that are correlated with both audit quality and firm innovation? Would firms with great innovation achievements be more likely to hire high audit quality services? To address these endogeneity concerns, we conduct a battery of tests as follows.

First, we follow Jayaraman and Milbourn (2015) and use the Enron/Andersen collapse as a quasi-natural experiment of forced auditor changes that affects audit quality. In 2001-2002, the Enron scandal of accounting frauds led the energy giant Enron Corporation to bankruptcy, and its auditor, Arthur Andersen, one of the top auditors worldwide, to collapse. As a result, Arthur Andersen's clients had been forced to change their auditors (Barton, 2005). This event can be considered a quasi-natural experiment that creates plausibly exogenous variation in audit quality for these former Andersen's clients (i.e., treatment firms). We use a difference-in-differences approach (DiD) to compare the innovation output of these treatment firms with that of control firms which do not experience the exogenous variation in audit quality. We find that compared to control firms, treatment firms generate a larger number of patent counts and patent citations, suggesting that the negative effect of audit quality on firm innovation appears to be causal.

Second, prior work suggests that audit quality may be endogenously determined due to self-selection bias based on certain firm characteristics (Chang et al., 2009). To address this endogeneity concern, we follow Chang et al. (2009) and apply the Heckman (1979)'s selection model to a firm's auditor choice in a given year. We find that the negative effect of audit quality on firm innovation remains robust to this estimation approach.

Apart from these tests, we conduct further robustness checks to validate the impact of audit quality on firm innovation. Specifically, we follow the literature (e.g., DeFond et al., 2016) and use alternative measures for audit quality, which include audit fees, industry specialist auditors, and going-concern opinions. Again, we find consistent evidence. For further robustness tests, we re-estimate the baseline regression model using different subsamples, such as a subsample of firms that have at least one patent during the sample period, a subsample of non-Big 4 clients, and a subsample of firms having long auditor tenure. We continue to find consistent evidence for the negative effect of audit quality on firm innovation.

After establishing the effect of audit quality on innovation, we attempt to explore possible mechanisms through which audit quality hinders firm innovation. First, we find that firms with high audit quality have more analyst coverage. In addition, Andersen clients switching to non-Big 4 auditors after the Andersen collapse have less analyst coverage. Given that financial analysts serve as a hindrance to firm innovation by imposing short-term pressure on managers (He and Tian, 2013), our findings suggest that analyst coverage is a plausible channel through which audit quality negatively affects firm innovation. As audit quality is lower in a firm that switches from Andersen to a non-Big 4 auditor, so is the analyst coverage of that firm: less analyst coverage can alleviate managerial myopia by placing less short-term pressure on managers, thus leading to more investment in long-term innovative projects.

Second, we find that firms with high audit quality have greater equity ownership by non-dedicated institutional investors. Further, Andersen clients attract fewer non-dedicated institutional investors after switching to non-Big 4 auditors. To the extent that these institutions increase the probability that managers reduce R&D investments to manage earnings (Bushee, 1998), our findings suggest that greater ownership by non-dedicated institutional investors is another plausible mechanism underlying the negative effect of audit quality on firm innovation. Specifically, the managers of firms experiencing exogenous variation in audit quality due to the Andersen collapse are subject to less exposure to short-term pressures from these investors. Accordingly, they have stronger incentives to invest in long-term innovative projects, which eventually results in higher innovation output.

The rest of the paper is organized as follows. Section 2 discusses the related literature. Section 3 describes the sample, variable construction, and descriptive statistics. Section 4 reports the baseline results. Section 5 addresses endogeneity issues. Section 6 provides robustness tests. Section 7 discusses possible mechanisms. Section 8 concludes the paper.

2. Relation to the existing literature

We make contributions to two strands of literature. First, our study adds to the literature on motivating firm innovation. Manso (2011) shows that managerial contracts that tolerate failure in the short term and reward success in the long term are best at motivating technological innovation. Empirical research has documented factors contributing positively to firm innovation, such as overconfident CEOs (Hirshleifer et al., 2012), institutional investor holdings (Aghion et al., 2013), corporate venture capital (Chemmanur et al., 2014), non-executive employee stock options (Chang et al., 2015), and foreign institutional investors (Luong et al., 2016). On the contrary, prior research also documents various barriers to firm innovation, such as a creditor-friendly code (Acharya and Subramanian, 2009), antitakeover law (Atanassov, 2013), financial analysts (He and Tian, 2013), and stock liquidity (Tian and Wang, 2014). However, extant literature still remains silent on the roles of audit quality in firm innovation. We fill this gap by documenting a negative effect of audit quality on innovation as measured by the number of patents granted and the number of citations made to these patents.

Our study is also related to the auditing literature. On the positive side, high audit quality can mitigate informational asymmetry between informed managers and uninformed capital suppliers regarding the firms' future prospects (Abdel-Khalik and Solomon, 1988), which in turn enables the firms not only to borrow at a lower cost (Mansi et al., 2004) but also to have a better access to financing resources (Chang et al., 2009; Kausar et al., 2016). Moreover, high audit quality allows for fewer and less restrictive debt covenants by providing assurance to the lenders at the contract inception, which ensures a lower probability of actual covenant violations (Robin et al., 2016). High audit quality can also shorten the restatements' dark period when a company finds that it needs to restate financial data to the subsequent disclosure (Schmidt and Wilkins, 2013). Kanagaretnam et al. (2016) find that high audit quality is negatively associated with the likelihood of corporate tax aggressiveness. Kim et al. (2015) argue that firms with high audit quality are often associated with a higher market value of cash holdings due to the monitoring device of external auditing.

On the down side, high audit quality raises a firm's visibility in the financial markets and thus subjects it to a higher likelihood of becoming a target for mergers and acquisitions (Yuan et al., 2013). Under greater takeover pressure, the manager may focus on short-term earnings targets at the expense of long-term innovative investments. Although external auditors are a key determinant of financial information quality (e.g., Abdel-Khalik and Solomon, 1988), there is scant evidence on the effect of audit quality on their clients' long-term innovative projects. We extend this literature by documenting novel evidence on the negative impact of audit quality on firm innovation.

Our paper is closely related to Chang et al. (2013), who find a negative effect of accounting conservatism on firm innovation. Their findings are consistent with ours in that financial report quality places substantial short-term pressure on managers, thus reducing their incentives to invest in long-term innovative projects. However, we differ from them by focusing on audit quality rather than accounting conservatism.

3. Sample selection and descriptive statistics

3.1. Sample Selection

We obtain data from several sources. Data on firm innovation are from Kogan et al. (2016), which contains more than four million patents issued to U.S. firms from 1926 to 2009. Data on audit quality are from AuditAnalytics, which provides auditor history details, auditor changes, as well as auditor fees disclosed by SEC registrants in electronic filings since January 2000. The data have been extracted primarily from the proxy statement 14A, 10Ks, 20Fs, 40Fs and N-CSR filings. Thus, our sample period is from 2000 to 2009 because AuditAnalytics data are only available from 2000 onwards and firm innovation data are available up to 2009.

We collect accounting data from Compustat Annual Files, institutional holdings data from Thomson Reuters Institutional Holdings (13f), analyst coverage data from the Institutional Brokers' Estimate System (I/B/E/S) database, stock price information from the Centre for Research in Security Prices (CRSP), the institutional investor classification data from Brian Bushee's website.[2] We exclude firms in the financial (two-digit SIC codes 60 to 69) and public utility (two-digit SIC code 49) industries because they are highly regulated. Our final sample has 35,460 firm-years observations with 7,482 unique firms.

3.2. Variables and Their Measurements

3.2.1. Firm Innovation

Earlier literature often uses innovation input such as R&D expenditures to proxy for long-term investment because their costs are easily extractable from corporate financial data (e.g., Bushee, 1998; Kimbrough, 2007; Lerner and Wulf, 2007; Li, 2011). However, R&D expenditures do not necessarily lead to better long-term investment performance because of uncertainty, agency issues, and managerial over-optimism (Horwitz and Kolodny, 1980). Changes in R&D expenditures are even harder to interpret (Jensen, 1993; Muelbroek et al., 1990). Therefore, following recent literature (Kogan et al., 2016; Seru, 2014), we adopt innovation output measures such as patent counts and non-self citations of patents. The most recent version of patent database constructed by Kogan et al. (2016) contains information about patent number, patent assignees and its CRSP-matched identifiers (*permno*), the number of citations received by each patent, the technology class of the patents, and the year patents applied for and the year patents granted. The database chases the entire history of U.S. patent documents from Google Patents. Kogan et al. (2016)'s patent data set is comparable to the data set of the National Bureau of Economics Research (NBER) 2006 patent project since it provides a matched *permno* for 31% of all granted patents while that of NBER is 32% from 1976 to 2006. Moreover, Kogan et al.'s database is superior to the NBER database because the former provides more updated patent data (up to year

[2] http://acct.wharton.upenn.edu/faculty/bushee/.

2009 compared to 2006) and covers more firms (27% of its patents is not covered by the NBER database).

Our first measure is the number of patents applied for in a given year by a firm that is eventually granted, which represents the quantity of innovation production. Our second measure is the sum of the number of non-self citations received on each granted patent in a given year during our sample period, which measures innovation quality. We adjust patent citations for the technology class after Hall et al. (2001) by dividing each patent's citation counted by the average citation of all patents filed (and eventually granted) in the same cohort (same two-digit technology class and application year). This measure of innovation quality takes into account the non-uniform propensity for patents in different technology classes to cite other patents.

The distributions of the numbers of patent counts and their citations are extremely right-skewed, with the 75th percentile of its distribution at zero. Hence, we use the natural logarithm of 1 plus patent counts (PAT) and the natural logarithm of 1 plus patent citations (CIT) as our measures of firm innovation.

While patent counts and patent citations are good measures of long-term investment output, they also have limitations. Innovation can have various propensity and duration which leads to the difficulty in comparing the level of innovativeness between industries (Hall et al., 2001). For example, the innovation process by nature is more time-consuming in the pharmaceutical industry than in the technology industry. We may observe fewer patents granted in pharmaceutical industry in a given period of time, but it does not necessarily signify the different levels of innovativeness between the two industries. However, we aim to control adequately for heterogeneity across firms and industries in order to alleviate this concern.

3.2.2. Audit Quality

According to DeFond and Zhang (2014), audit quality improves financial reporting quality by increasing the credibility of the financial reports. Existing literature uses a large number of proxies to measure audit quality. However, there is no consensus on which measure is the best. Since a firm's auditor choice is extensively adopted in the literature (e.g., Behn et al., 2008; Chang et al., 2009; Francis et al., 2014), we use $BIG4$ as our main variable for audit quality, where $BIG4$ equals 1 if a firm selects a Big 4 account firm as its auditor in a fiscal year, and 0 otherwise.[3]

The Big 4 auditors differentiate their audit quality from small audit firms (Becker et al., 1998; Eshleman and Peng, 2014). They have both incentives and competency to assure integrity of disclosed information to maintain their reputation (DeAngelo, 1981). Financial markets also perceive that firms audited by Big 4 auditors enjoy a higher audit quality of information disclosure and lower uncertainty about future cash flows (Chang et al., 2009). Furthermore, DeFond et al. (2016) reassure that the Big N effect persists under a majority of propensity score matching's (PSM's) research design choices and across several commonly used audit quality proxies although a few studies suggest that the Big N effect disappears under the PSM (Chaney et al., 2004; Petroni and Beasley, 1996). To a certain extent, Big 4 is a good measure of audit quality.

Although audit quality, as proxied by Big 4 membership, is often argued to capture strong auditor incentives to provide high quality services, we acknowledge that this measure has some weaknesses. According to DeFond and Zhang (2014), the membership of Big 4 is unable to capture subtle differences in the demand of audit quality. We, therefore, employ alternative audit quality proxies, namely, audit fees, industry specialists, and going concern opinions to validate our results.

[3] We classify auditors into Big 4 and non-Big 4 accounting firms. Big 4 firms include Ernst & Young, Deloitte & Touche, KPMG, and PricewaterhouseCoopers. If we add Arthur Andersen into consideration to form Big 5 for the period of 2001-2002 before Arthur Andersen's collapse, our results remain consistent.

3.2.3. Control variables

Following existing literature on technological innovations (Fang et al., 2014; He and Tian, 2013), we control for various firm- and industry- characteristics that may influence a firm's innovation productivity. The control variables which are calculated for firm *i* over its fiscal year *t* include: Firm size, MV, market value of a firm, measured by the natural logarithm of the firm's market capitalization; Profitability, ROA, return on assets; Investments in innovation, RD, R&D expenditures scaled by total assets; Asset tangibility, PPE, net property, plant and equipment scaled by total assets; Leverage, LEV, the ratio of total debt to total assets; Investment in fixed assets, $CAPEX$, capital expenditure scaled by total assets; Institutional ownership, $INST$, the arithmetic mean of the four quarterly institutional holdings scaled by firm's share outstanding; Analyst coverage, ANA, the natural logarithm of one plus arithmetic mean of the 12 monthly earnings forecasts; Amihud (2002)'s liquidity, $ILLIQ$; Product market competition, HHI, Herfindahl index based on annual sales; Growth opportunity, Q, measured by Tobin's Q; Financial constraints, KZ, the five-variable KZ index of Kaplan et al. (1997); Firm age, AGE, natural logarithm of one plus the number of years the firm is listed on Compustat. We also include the squared Herfindahl index, $HHISQ$, in our baseline regression to address nonlinear effects of product market competition, in line with Aghion et al. (2005). To reduce the influence of outliers, all continuous variables are winsorized at the 1% and 99% levels. Detailed variable definitions are provided in Appendix A.

3.3. Descriptive statistics

Panel A of Table 1 provides the descriptive statistics of the main variables in this study. An average firm in our sample has 11.21 granted patents per year and receives 11.14 non-self citations. There are 75.1% of the sample firms using Big 4 auditors. On average, a firm has market capitalization of $194.76 million, R&D expenditure of 7.0%, asset tangibility of 25.2%, leverage level of 26.4%, a Tobin's Q of 2.55 and is 13.7 years old since data recorded in Compustat. These firm characteristics are, on average, consistent with those reported in the existing literature. The correlation matrix of these variables is reported in Appendix B.

(INSERT TABLE 1 HERE)

Panel B of Table 1 reports the numbers and the percentages of innovative and non-innovative firms across industries, where a firm is defined as innovative (non-innovative) if it has at least one (does not have any) granted patent during the sample period. Using Fama-French 12-industry classification retrieved from Kenneth French's website,[4] we find that firms with patents scatter across these industries. Health industry is the most innovative one with the largest proportion of innovative firms (46%) while Wholesale, Retail and some Services (Laundries, Repair Shops) is the least innovative one with the smallest proportion of innovative firms (9%). Consumer durables, Manufacturing and Business Equipment are relatively innovative compared to the other industries as their innovative firms account for 44%, 41%, and 38% of the sample firms, respectively. Overall, 28% of the sample firms are innovative ones.

4. Baseline Empirical Results

4.1. Impact of Audit Quality on Firm Innovation

We first explore the impact of a firm's audit quality on its innovation by estimating various forms of the following pooled Ordinary Least Squares (OLS) regression model:

$$PAT_{i,j,t+n}\left(CIT_{i,j,t+n}\right) = \alpha + \beta BIG4_{i,j,t} + \gamma X_{i,j,t} + \phi_i + \omega_j + \varphi_t + e_{i,j,t+n}, \tag{1}$$

[4] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_12_ind_port.html.

where *i*, *j*, and *t* refers to firm, industry, and year, respectively, and *n* equals 1, 2 or 3. The dependent variable captures firm innovation outcome: the natural logarithm of 1 plus the number of granted patents (PAT) or the natural logarithm of 1 plus the number of non-self citations adjusted for technology class (CIT). Our main explanatory variable, $BIG4$, is a dummy variable measuring audit quality, which equals 1 if a firm is audited by a Big 4 auditor in a given fiscal year, and 0 otherwise. X denotes a vector of firm and industry characteristics that can affect firm innovation productivity as discussed in Subsection 3.2.3. We include year fixed effects (φ) to account for inter-temporal variation that may affect the relationship between audit quality and innovation, and firm fixed effects (ϕ) or industry fixed effects (ω) in various specifications. As innovation output is likely to be auto-correlated, we cluster standard errors by firm in all regressions to avoid inflated *t*-statistics. We report the regression results of Equation (1) in Table 2.

(INSERT TABLE 2 HERE)

Panel A of Table 2 provides OLS regression results from estimating Equation (1), controlling for industry fixed effects using 2-digit SIC codes and year fixed effects. The coefficient estimates on $BIG4$ are negative and statistically significant at the 1% level across all specifications. This indicates a negative relationship between audit quality and firm innovation. In terms of the economic significance, the coefficient estimates on $BIG4$ in columns 1-3 suggest that a firm's patent counts decline by 13.9%, 15.7% and 16.7% in the one-, two-, and three-years after being audited by a Big 4 auditor, respectively. Similarly, the coefficient estimates on $BIG4$ in columns 4-6 suggest that a firm's patent citations decrease by 13.6%, 15.4% and 16.1% in the one-, two-, and three-years after being audited by a Big 4 auditor, respectively.

While pooled OLS regression results show a negative association between audit quality and firm innovation, one concern is that these results could be driven by omitted variables. To mitigate this concern, we include firm fixed effects and at the same time drop industry fixed effects in Panel B of Table 2. Firm fixed effects absorb time-invariant unobservable firm characteristics that affect both audit quality and firm innovation. We continue to find that the coefficient estimates on $BIG4$ are negative and statistically significant at the 1% level across all specifications. The magnitudes of these coefficient estimates are slightly smaller but comparable to those in Panel A. This evidence suggests that our finding is not driven by time-invariant unobservable firm characteristics.

Regarding the control variables, larger and older firms are associated with higher innovation output. Firms with more capital expenditures are more innovative. Competition in the industry stimulates firm innovation at a decreasing rate as the coefficient estimates on HHI are positive and statistically significant and coefficient estimates on $HHISQ$ are negative and statistically significant in firm fixed effects regression (Panel B of Table 2). These findings are consistent with earlier work (Hall and Lenner, 2010).

To check whether our results are driven by a specific industry or not, we re-estimate Equation (1) for each of the Fama-French industry using the OLS regressions with firm and year fixed effects. For brevity, we report only the coefficient estimates on $BIG4$ in Panel C of Table 2, which are negative and mostly significant across all industries. Therefore, the negative relationship between audit quality and firm innovation is held for almost all industries.

In sum, this subsection shows a negative effect of audit quality on firm innovation, which supports our first hypothesis that audit quality adversely affects firm innovation.

4.2.Changes in Audit Quality and Changes in Firm Innovation

This subsection extends the previous subsection's analysis by explicitly investigating the effect of the change in a firm's auditor on the change in its innovation. According to our first hypothesis for the adverse effect of audit quality on firm innovation, a decrease (an increase) in audit quality should lead to an improvement (a reduction) in firm innovation. Following Mansi et al. (2004), we examine the number of auditor changes. We exclude all auditor changes made by Andersen's clients here due to its unique nature of forced changes, which is a subject of a separate analysis below. In our sample, there are 77 firms switching up from non-Big 4 auditors to Big 4 auditors, 377 firms switching down from Big 4 auditors to non-Big 4 auditors, 523 firms changing auditors among Big 4 auditors and 661 firms changing auditors among non-Big 4 auditors.

To examine the effect of changes in auditors on firm innovation, we estimate the following cross-sectional model:

$$\Delta PAT_{i,t}\left(\Delta CIT_{i,t}\right) = \alpha + \beta UP_{i,t} + \lambda DN_{i,t} + \pi \Delta BIG4_{i,t} + \tau \Delta NBIG4_{i,t} + \gamma \Delta X_{i,t} + e_{i,t}, \qquad (2)$$

where ΔPAT (ΔCIT) measures the change a firm's innovation outputs in the years after and before an auditor change. In Equation (2), dummy variable UP equals 1 if a firm switches from a non-Big 4 auditor to a Big 4 auditor and 0 otherwise, DN equals 1 if a firm switches from a Big 4 auditor to a non-Big 4 auditor and 0 otherwise, $\Delta BIG4$ equals 1 if a firm switches between Big 4 auditors and 0 otherwise, and $\Delta NBIG4$ equals 1 if a firm switches between non-Big 4 auditors and 0 otherwise.

We report the regression results of Equation (2) in Table 3. The results show that the coefficient estimates on DN are positive and statistically significant at the 1% level in column 1 and at the 5% level in column 2, which suggests that firms changing from Big 4 to non-Big 4 auditors experience increases in both patent counts and patent citations. We cannot draw a decisive conclusion regarding firms that switch from non-Big 4 to Big 4 auditors since the coefficient estimates on UP are positive but statistically insignificant at the conventional level. We also find that both patent counts and patent citations increase for firms switching their auditors among non-Big 4 ones as the coefficient estimates on $\Delta NBIG4$ are positive and significant. However, the coefficient estimates on $\Delta BIG4$ are not significant, suggesting that there is no clear evidence for the effect of the change in auditors among Big 4 one on firm innovation.

(INSERT TABLE 3 HERE)

To conclude, this subsection shows that firms switching from Big 4 to non-Big 4 auditors experience subsequent increases in both patent counts and patent citations, which again supports our first hypothesis that the audit quality of firm adversely affects its innovation.

5. Addressing Endogeneity Issues

5.1. Quasi-natural experiment –Enron/Andersen Collapse

Similar to Jayaraman and Milbourn (2015), we use the Andersen collapse as a quasi-natural experiment of forced auditor changes that influence audit quality. The Enron scandal of wrongly reporting $100 billion in revenue was revealed in October 2001. It eventually led to the bankruptcy of the Enron Corporation, an American energy company, and the dissolution of Arthur Andersen, which was one of the five largest auditing firms in the world at the time. Since then, Arthur Andersen sold most of its U.S. operations to other accounting firms and stopped practicing in August 2002. Arthur Andersen’s clients had been forced to change their auditors within the short period of time following the Enron/Andersen Collapse (2001-2002) and “client defections most likely reflected concerns about the auditor's reputation and ability to provide quality services rather than changes in clients' operating, financing, and investing activities” (Barton, 2005). Thus, auditor switches in this setting are most likely the result of an exogenous shock to audit quality, which can be considered a quasi-natural experiment for studying whether exogenous variation in audit quality lead to an increase or a decrease in firm innovation.

We use a difference-in-differences approach to compare the innovation output of treatment firms with that of control firms before and after the Andersen collapse. To select treatment firms, we first require these firms to be Andersen clients before the collapse and then make a change to non-Big 4 auditor right after the collapse. To select the control firms, we require firms to be non-Andersen clients and be audited by Big 4 auditor before the collapse. This filter leaves us with 28 treatment firms and 248 control firms before matching.

We then match each treatment firm with five control firms using the nearest neighbor propensity score matching algorithm (PSM). Specifically, we estimate a probit model for observations in 2001, the year immediately preceding the Andersen collapse. The dependent variable equals 1 if the firm-year observation belongs to the treatment group, and 0 otherwise. The probit regression has the same set of control variables in the baseline regression, including industry dummies. We also add two innovation growth variables, namely, PAT_GROWTH and CIT_GROWTH, computed over the years before 2002, to ensure the satisfaction of the parallel trend assumption, which is a key identifying assumption of DiD approach.[5]

We estimate the probit model parameters and provide the regression result in column (1) of Table 4, Panel A. The results show that the specification captures a significant amount of variation in the choice variable, as indicated by a pseudo-R^2 of 46.9% and a *p*-value from the χ^2 test of overall model fitness well below 0.001. We then apply the propensity scores obtained from using estimated probit model of column (1) to perform nearest-neighbor propensity score matching. In

[5] This assumption states that in the absence of the treatment (the collapse of Andersen in our settings), the observed DiD estimator is zero. The parallel does not require the level of outcome variables (innovation output) to be identical across treatment and control firms, because these distinctions are differenced out in the estimation. Instead, this assumption requires similar trends in innovation variables during the pre-event for both treatment and control groups.

particular, each treatment firm is matched with five firms that have the closest propensity scores in the control groups. We end up with 24 unique treatment firms and 30 unique control firms after matching.

As the validity of the DiD estimate critically relies on the parallel trends assumption, we implement a number of diagnostic tests to verify that we do not violate the assumption. In the first test, we re-estimate the probit model, restricted to the matched sample and present the results in column (2) in Panel A of Table 4. Most of the independent variables are statistically insignificant. Specifically, the coefficient estimates on the innovation growth variables are not statistically significant, suggesting that there are no observable different trends in innovation outputs between the two groups of firms. In addition, the pseudo R^2 drops drastically from 46.9% prior to the matching to 33% after the matching.

(INSERT TABLE 4 HERE)

In our second diagnostic test, we report in Panel B of Table 4 the univariate comparisons between treatment and control firms' pre-Andersen collapse characteristics and their corresponding t-statistics. We observe that none of the observed differences between the treatment and control firms' characteristics is statistically significant before the collapse of Andersen. The univariate comparison between innovation growth variables suggests that the parallel trends assumption is not violated. Overall, the diagnostic tests reported above indicate that the propensity score matching procedure removes meaningful observable differences. This increases the likelihood that the changes in innovation are caused only by the exogenous change in audit quality due to the Andersen collapse.

We then perform the DiD regression by estimating the following model:

$$PAT_{i,j,t+n}\left(CIT_{i,j,t+n}\right) = \alpha + \beta TREAT_i * POST_t + \gamma X_{i,j,t} + \omega_j + \varphi_t + e_{i,j,t+n}, \tag{3}$$

where i, j and t refer to firm, industry and year, respectively, $TREAT_i$ is a dummy variable that equals 1 for treatment firms, and 0 for control firms, $POST_t$ is a dummy variable that equals 1 if the fiscal year is after 2002 (the year of Andersen collapse), and 0 otherwise. The coefficient β is the DiD estimator that captures the causal effect of the Andersen-induced auditor change on firm innovation.

We report the regression results in Panel C of Table 4 with standard errors clustered at the firm level. The coefficient estimates on $TREAT * POST$ (β) are positive and statistically significant at the 5% level across all specifications, indicating that treatment firms (Andersen clients that switch to non-Big 4 auditors following the collapse), on average, experiencing a larger improvement in future innovation output than those of the control firms after the collapse. The coefficient estimates of 0.135, 0.143, and 0.153 in columns 1-3 imply that, compared with control group, the treatment group increases in their patents by 13.5%, 14.3%, and 15.3% in the first, second and third year after the event, respectively. Similarly, coefficient estimates of 0.097, 0.127, and 0.122 in columns 4-6 indicate that compared to control firms, treatment firms increase their citations by 9.7%, 12.7% and 12.2% in each of these three years.

In short, this subsection shows that firms switching from Andersen to non-Big 4 auditors following the Andersen collapse generate a larger number of both patent counts and patent citations, which is consistent with the claim that the negative effect of audit quality on firm innovation appears to be causal.

5.2. Heckman Selection Model

The choice of auditor may be endogenously determined by firm self-selection based on certain characteristics. To address this issue, we adopt a two-stage Heckman (1979)'s approach to analyze auditor choice. In the first stage, we estimate a probit model predicting the likelihood of hiring a Big 4 auditor in a given fiscal year by regressing $BIG4$ on a number of relevant variables. Similar to Chang et al. (2009), the explanatory variables in this probit model include all control variables used in regression (1), and additional variables: the total assets turnover ratio ($TATURN$), measured as the net sale divided by total assets; research and development dummy (RDD) equals 1 if the value of research and development expenses is missing for the firm, and 0 otherwise; total assets growth rate (TAG); the ratio of current assets to total assets (CA). In the second stage, we re-estimate Equation (1) using the fitted value of $BIG4$ *(Predicted_BIG4)* from the first-stage regression instead of $BIG4$. We also add the inverse Mills ratio (IMR) to the regression. We report the regression results in Table 5.

(INSERT TABLE 5 HERE)

We find that the estimated coefficients of *Predicted_BIG4* are all negative and significant at the 1% level. Regarding the economic significance, the coefficients in columns 1-3 indicate that firms reduce their patent counts by 8.3%, 9.9% and 11.3%, respectively, in the first, second and third year after it is audited by a Big 4 auditor. Similarly, the coefficient estimates on $BIG4$ in columns 4-6 indicate that firms reduce their patent citations by 8.1%, 9.9% and 10.5% in each of these three years. Thus, the Heckman selection model confirms the negative effect on audit quality on firm innovation, which is consistent with our earlier baseline findings.

6. Further Analysis

In this section, we validate the negative relationship between audit quality and firm innovation using alternative measures of audit quality and different subsamples of firms.

6.1. Alternative Measures of Audit Quality

Although the choice of a Big 4 auditor is widely used in prior literature to measure audit quality, there is a concern that it is a choice variable which implicitly assumes a homogeneous level of audit quality within each group of auditor selection (Clarkson and Simunic, 1994; DeFond and Zhang, 2014). Moreover, one may argue that firms appointing a Big 4 auditor are among those that are quite mature, and thus the Big 4 effect merely reflects the firms' life cycle on innovation. To address this issue, we use alternative measures of audit quality and re-examine the effects of these measures on firm innovation.

Wang et al. (2008) contend that audit fees represent audit capability to detect accounting errors and incentive to provide audit services with better quality. We thus use audit fees as our first alternative proxy for audit quality. Data on audit fees are obtained from AuditAnalytics and this measure ($AUDIT\_FEE$) is defined as the natural logarithm of the audit fees in a given fiscal year.

Our second alternative measure of audit quality is industry specialist auditors ($SPEC$). Previous literature documents a positive association between industry specialist auditors and audit quality (Balsam et al., 2003; Reichelt and Wang, 2010). In particular, industry specialist auditors are perceived to be more resilient, more confident, and less influenced by managers in their assessment of the validity of the accounting methods and estimates embedded in financial statements (Krishnan, 2005). Following Godfrey and Hamilton (2005), we define an industry specialist auditor variable ($SPEC$) for firm *i* in industry *j* in a given fiscal year as sales for all firms in industry *j* that are audited by the same auditor in that year as firm *i*, scaled by sales for all firms in industry j.

Our measures of audit quality such as auditor choice and fees of auditing services are based on observable inputs to the audit process. To capture the output of the audit process, we choose going-concern opinions as our third alternative proxy for audit quality. Auditors should issue a going-concern opinion when a firm's financial condition casts doubt on its ability to continue. Prior literature suggests that the issuance of a going-concern opinion is an indicator of low audit quality (Aobdia, 2016; Bowler, 2015; Fogel-Yaari and Zhang, 2013; Kaplan and Williams, 2013). Thus, we collect going-concern opinions from AuditAnalytics and follow DeFond et al. (2016) to define a going-concern opinion variable (GC) as a dummy variable, which equals 1 if firm's auditor issued a going-concern opinion, and 0 otherwise.

(INSERT TABLE 6 HERE)

Using these three alternative measures of audit quality, we re-estimate the baseline regression equation (1) and present the results in Table 6. Apparently, the coefficient estimates on $AUDIT\_FEE$ in Panel A and those on $SPEC$ in Panel B are all negative suggesting that firms higher audit fees or audited by industry specialists (high audit quality) are associated with fewer patents and citations. Whereas, coefficient estimates on GC in Panel C are all positive indicating that firms with going-concern opinions (low audit quality) have more patents and citations. All these estimates are significant at the 1% levels, suggesting that these alternative measures of audit quality lead to consistent results with the baseline model.

6.2. Different Subsamples

One concern drawn from our baseline regression results is the sample selection biases. To address this issue, we conduct three subsample analyses as follows.

First, in order to rule out the possibility the results are driven by a large number of firm-year observations with zero patents and citations, we focus on a subsample of firms having at least one patent during the sample period and re-estimate the regression model (1). We document the results in Panel A of Table 7. We find that the coefficient estimates on $BIG4$ are negative and statistically significant at the 1% level, suggesting that among all innovative firms, a firm with high audit quality has fewer future patent counts and patent citations.

(INSERT TABLE 7 HERE)

Second, the choice of a Big 4 or a non-Big4 auditor may merely capture the auditor size rather than audit quality. To address this concern, we re-estimate the regression model (1) for a subsample of firms that are audited on only non-Big 4 auditors during the sample period. Among non-Big 4 auditors, larger non-Big 4 auditors may provide higher audit quality compared to the other smaller non-Big4 auditors. Therefore, we follow Chang et al. (2009) and partition non-Big 4 auditors into large non-Big 4 versus small non-Big 4 ones. Specifically, we select Grant Thornton, BDO Seidman, Crowe Chizek and McGladrey & Pullen as 4 large non-Big 4 auditors, and define a dummy variable ($LARGE\_NON\_BIG4$), which equals 1 if firms are audited by a large non-Big 4 auditor in a fiscal year, and 0 otherwise. Panel B of Table 7 documents the regression results using this subsample. We find that the coefficient estimates on $LARGE\_NON\_BIG4$ are statistically insignificant, which indicates that firms audited by a large non-Big 4 auditor have no significant differences in their innovation output, as compared with their counterparts that are audited by a smaller non-Big 4 auditor. Such evidence further underscores the unique adverse effect of Big 4 auditors on firm innovation.

Third, we follow extensive prior research (Caramanis and Lennox, 2008; Chang et al., 2009; El Ghoul et al., 2016; Guedhami et al., 2014; Lennox and Pittman, 2010; Myers et al., 2003) and focus on a subsample of firms having long auditor tenure. Prior studies suggest that a long auditor tenure may lessen information asymmetry between the auditor and the firm, and hence lead to better audit quality (Caramanis and Lennox, 2008). We define a firm having a long auditor tenure if the minimum auditor tenure is five years, after Lennox and Pittman (2010) and El Ghoul et al. (2016).[6] We-estimate the regression model (1) for this subsample and report the results in Panel C of Table 7. We continue to observe that the coefficient estimates on $BIG4$ remain negative and

[6]In un-tabulated re-estimations, we find supportive evidence at the 1% level when we modify alternative cut-off point from two to seven years to identify long-tenure clients.

statistically significant at the 1% level, indicating that within the subsample of firms with a long auditor tenure, a firm with the Big 4 auditor has fewer future patent counts and patent citations. Overall, these subsample analyses suggest that the negative effect of audit quality on firm innovation remain robust to different subsamples.

7. Possible Economic Mechanisms

To explain how the audit quality of a firm has a negative effect on firm innovation, this section discusses possible economic mechanisms underlying this effect. These underlying channels are not necessarily mutually exclusive, and may jointly contribute to the negative effect of audit quality on innovation.

7.1. Analyst Coverage

The first possible mechanism is a firm's analyst coverage. The good audit quality of a firm resulting in better financial reporting can attract more analysts to follow the firm as they rely on historical financial statements to forecast the firm's future performance (Lang and Lundholm, 1996). Nevertheless, firms covered by a larger number of financial analysts generate fewer future innovation outputs, as argued by He and Tian (2013). Likewise, Graham et al. (2005) show that top managers with more following analysts tend to focus more on short-term earning goals to meet analysts' targets rather than to invest in long-term innovative projects in order to maintain their wealth, career and other external reputation concerns. Thus, analyst coverage could be an underlying economic mechanism that helps explain the negative effect of audit quality on innovation.

To examine whether financial analysts play a role for the negative effect of audit quality on firm innovation, we first examine the relationship between analyst coverage and audit quality using a multivariate regression as following model:

$$ANA_{i,j,t+1} = \alpha + \beta BIG4_{i,j,t}\ (TREAT_i * POST_t) + \gamma X_{i,j,t} + \omega_j + \varphi_t + e_{i,j,t+1}, \qquad (4)$$

where the dependent variable, ANA, measures the analyst coverage as explained in Appendix A. The key explanatory variable is either $BIG4$ or $TREAT * POST$, other explanatory variables include research and development expenses (RD), firm size (MV), leverage (LEV), profitability (ROA), capital expenditure ($CAPEX$), trading volume ($TRADE$), advertising expenses ($ADVER$), return volatility (SD), reciprocal of stock price ($RECIP\_P$), shareholder base (SH_BASE) and inclusion in S&P 500 (SP_500), which are constructed in the same way as those in Jiraporn et al. (2014). The specification includes industry fixed effects ω_j and year fixed effects φ_t.

(INSERT TABLE 8 HERE)

We first estimate Equation (4) using the entire sample where the key independent variable is $BIG4$ and report the results in column (1) of Table 8. We find that the coefficient estimate on $BIG4$ is positive and statistically significant at the 1% level. This finding implies that firms with high audit quality attract more analyst coverage.

We also estimate the relationship between audit quality and analyst coverage using a DiD regression framework as in Section 5.1. Using the subsample of treatment and control firms constructed based on the Andersen collapse, we estimate Equation (4) with $TREAT * POST$ as the key explanatory variable and report the results in column (2) of Table 8. The coefficient estimate on $TREAT * POST$ captures the effect of an exogenous reduction in audit quality due to the Andersen collapse on analyst coverage. We find that the coefficient estimate on $TREAT * POST$ is negative and statistically significant at the 1% level, indicating that treatment firms are exposed to less analyst coverage compared to control firms. In other words, firms with lower audit quality have less analyst coverage.

Given our findings that audit quality negatively affects firm innovation and that financial analysts are a barrier to firm innovation by imposing short-term pressure on managers (He and Tian, 2013), our findings imply that financial analysts are the possible channel through which audit quality adversely affects firm innovation. More specifically, firms with lower audit quality attract fewer analysts and less analyst coverage can mitigate managerial myopia by placing less short-term pressure on management, leading to more investment in long-term innovative projects.

7.2. Non-dedicated Institutional Investors

Non-dedicated investors pursue short-term price appreciation and have few incentives to monitor firms' activities as suggested by Porter and Wayland (1992). Therefore, non-dedicated investors who rely on publicly available information (such as audited financial reports) to make investment decisions can be more attracted to firms with good audit quality. However, as they chase after short-term earnings, non-dedicated investors can impose pressure on managers to meet their expectation and retrench firms' investment in innovation (Bushee, 1998). Thus, non-dedicated institutional investors could be another underlying economic mechanism that helps explain the negative effect of audit quality on firm innovation.

We calculate levels of equity ownership by different types of institutional investors, including dedicated investors, quasi-indexers, and transient investors following Bushee (1998, 2001).[7] We then merge Bushee's classification with quarterly institutional holdings of U.S. firms from Form 13f. After He and Tian (2013), we group quasi-indexers and transient investors together as non-dedicated investors since they have weak incentives to produce information about firm's fundamentals.

[7] Based on Bushee's classification (1998, 2001), dedicated investors are characterized by concentrated portfolio holding and low portfolio turnover; quasi-indexers are those that follow indexing strategies and hold fragmented portfolio; and transient investors are those with high portfolio turnover and momentum trading.

We adopt a similar framework as in Section 7.1 and first examine the relationship between non-dedicated institutional investors and audit quality using the following regression.

$$NON\_DED_{i,j,t+1} = \alpha + \beta BIG4_{i,j,t}(\,TREAT_i * POST_t) + \gamma X_{i,j,t} + \omega_j + \varphi_t + e_{i,j,t+1}, \quad (5)$$

where dependent variable, NON_DED, is equity holding of non-dedicated investors as explained in Appendix A. The key explanatory variable is either $BIG4$ or $TREAT * POST$, other independent variables include research and development expenses (RD), firm size (MV), leverage (LEV), inclusion in S&P 500 (SP_500), growth opportunity (Q), stock liquidity ($ILLIQ$), market-adjusted return over prior year ($RETURN$), and firm age (AGE). These variables are constructed in a comparable way to those used in Bushee (2001).

(INSERT TABLE 9 HERE)

We first estimate Equation (5) using the entire sample and $BIG4$ as the key independent variable and report the results in column (1) of Table 9. We find that the coefficient estimate on $BIG4$ is positive and statistically significant at the 1% level. This confirms a positive relationship between audit quality and non-dedicated institutional ownership.

We also estimate the relationship between audit quality and non-dedicated institutional ownership using a DiD regression framework as in Section 5.1. Using the subsample of treatment and control firms constructed based on the Andersen collapse, we estimate Equation (5) using the key explanatory variable as $TREAT * POST$ and report the results in column (2) of Table 9. We find that the coefficient estimate on $TREAT * POST$ is negative and statistically significant at the 5% level. This implies that Andersen clients which switch to a non-Big 4 auditors after the exogenous shock attract fewer non-dedicated investors in comparison to firms that switch to a Big 4 auditor.

Given our findings that audit quality hinders firm innovation and that non-dedicated institutional investors by chasing for short-term earnings obstruct managers to invest in innovative projects (Bushee, 1998), our findings support the argument that the presence of non-dedicated institutional investors is another possible channel through which the negative effect of audit quality on firm innovation occurs. In particular, firms with lower audit quality attract fewer non-dedicated institutional investors, which in turn can moderate managerial myopia by reducing short-term pressure on managers, leading to more investment in long-term innovative projects.

8. Conclusion

Using a large sample of U.S. firms for the period from 2000 to 2009, we find a negative effect of audit quality on firm innovation. Further, when a firm switches from a Big 4 auditor to a non-Big 4 auditor, it can lead to an improvement in its innovation output.

To address endogeneity, we use several approaches, including a quasi-natural experiment of the Enron/Andersen's collapse together with a Heckman selection model. Our results show a causal, negative effect of audit quality on firm innovation. In addition, these results remain valid under various robustness tests, such as different subsamples and alternative measures of audit quality. We also document that financial analysts and non-dedicated institutional investors, who tend to pressurize managers to meet short-term earnings targets, are behind the negative effect of audit quality on firm innovation. Taken together, our study provides novel evidence on the negative effect of audit quality on firm innovation.

Although our results show a negative effect of audit quality on innovation output, we cannot completely rule out the possibility that audit quality can encourage firm innovation. This is because our results reflect only the net effect of audit quality on innovation as audit quality can either enhance or impede firm innovation. For the U.S., we find that audit quality impedes innovation.

An avenue for future research is to examine whether audit quality affects firm innovation in a cross-country study in the same way as it does in the U.S.

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Appendix A: Variables Definitions

Variable	Definition
Measures of innovation	
PAT	Natural logarithm of 1 plus total number of patents filed (and eventually granted) in a year;
CIT	Natural logarithm of 1 plus the total number of citations made to each patent in a year, scaled by the mean citation count received by each patent in the year for the technology groups to which the patent belongs.
Measures of audit quality and control variables used in baseline model	
BIG4	Dummy variable equals 1 if firm employs a Big 4 auditor or 0 otherwise;
ANA	Natural logarithm of 1 plus arithmetic mean of the 12 monthly earnings forecasts of a firm, extracted from the Institutional Brokers' Estimate System (IBES) summary file;
INST	Institutional holdings (percent), which is the arithmetic mean of the four quarterly institutional holdings reported in Thomson's CDA (Form 13F);
ILLIQ	Amihud (2002)'s measure of stock illiquidity;
MV	Natural logarithm of market value of equity (#25×#199);
RD	Research and development expenditure (#46) divided by book value of total assets (#6);
ROA	Return on assets defined as operating income before depreciation (#13) divided by book value of total assets (#6);
PPE	Property, Plant & Equipment (net, #8) divided by book value of total assets (#6);
LEV	Leverage ratio, defined as book value of debt (#9+#34) divided by book value of total assets (#6);
CAPEX	Capital expenditure (#128) divided by book value of total assets (#6);
HHI	Herfindahl index of 4-digit SIC industry by sales (net, #12);
HHISQ	The squared HHI;
Q	Market-to-book ratio, calculated as [market value of equity (#199×#25) plus book value of assets (#6) minus book value of equity (#60) minus balance sheet deferred taxes (#74, set to 0 if missing)] divided by book value of total assets (#6);
KZ	KZ index, calculated as -1.002×Cash Flow ((#18+#140/#8) plus 0.283×Q plus 3.139×Leverage ((#9+#34)/(#9+#34+#216)) minus 39.368×Dividends ((#21+#19)/#8) minus 1.315×Cash holding (#1/#8), where #8 is lagged;
AGE	Natural logarithm of one plus firm age, approximated by the number of years listed on Compustat.
Measures of additional variables for examining mechanisms	
TRADE	Natural logarithm of the annual trading volume, data from CRSP;
ADVER	Advertising expenses (#45) divided by total assets (#6);
SD	The standard deviation of stock returns, calculated based on the monthly stock returns in the previous 12 months using data from CRSP;
RECIP_P	The reciprocal of the end-of-year stock price, based on data from CRSP;
SH_BASE	Natural logarithm of the number of common stockholders (#100);
RETURN	Market-adjusted stock return over prior year, based on data from CRSP;
SP_500	Dummy variable equals 1 if a firm is included in the S&P 500 Index, and 0 otherwise;
NON_DED	Institutional holdings (%) over fiscal year held by transient institutional investors and quasi-indexers.

Appendix B: Correlation of Main Variables

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
PAT	(1)	1.00																
CIT	(2)	0.98	1.00															
BIG4	(3)	0.22	0.21	1.00														
ANA	(4)	0.34	0.34	0.38	1.00													
INST	(5)	0.22	0.22	0.35	0.79	1.00												
ILLIQ	(6)	0.11	0.10	0.02	-0.09	-0.07	1.00											
MV	(7)	0.41	0.40	0.51	0.64	0.50	-0.10	1.00										
HHI	(8)	-0.02	-0.02	-0.07	-0.07	0.00	0.01	-0.07	1.00									
HHISQ	(9)	0.00	0.00	-0.06	-0.06	-0.01	0.01	-0.05	0.95	1.00								
RD	(10)	0.07	0.07	-0.06	-0.12	-0.15	0.07	-0.19	-0.10	-0.08	1.00							
ROA	(11)	0.09	0.09	0.27	0.25	0.26	-0.01	0.35	0.02	0.02	-0.54	1.00						
PPE	(12)	-0.10	-0.10	0.08	0.05	0.01	-0.04	0.14	-0.09	-0.05	-0.24	0.12	1.00					
LEV	(13)	-0.09	-0.09	-0.17	-0.12	-0.13	-0.04	-0.19	0.01	0.01	0.11	-0.46	0.14	1.00				
CAPEX	(14)	-0.06	-0.06	0.01	0.08	0.02	-0.04	0.11	-0.11	-0.08	-0.10	0.02	0.61	0.05	1.00			
Q	(15)	-0.02	-0.01	-0.23	-0.09	-0.13	-0.03	-0.10	-0.02	-0.02	0.39	-0.67	-0.10	0.44	0.03	1.00		
KZ	(16)	0.01	0.00	0.03	0.01	0.01	0.01	0.00	0.01	0.01	-0.03	-0.10	0.21	0.16	0.12	0.05	1.00	
AGE	(17)	0.15	0.14	0.08	0.15	0.25	-0.03	0.24	0.12	0.10	-0.16	0.20	0.09	-0.03	-0.06	-0.15	0.04	1.00

Table 1: Descriptive Statistics

Panel A dsiplays descriptive statistics of variables used in this paper, where the variables are measured from 2000 to 2009. Panel B reports the number and percentage of firms that generate at least one patent and zero patents over the sample period in each industry. Industries are defined following the Fama-French 12 industry group classification system. Utilities and Finance industries are excluded from the sample.

Panel A: Descriptive Statistics

Variable	5%	25%	Median	Mean	75%	95%	SD	Obs.
PAT	0.000	0.000	0.000	0.500	0.000	2.890	1.040	35,460
CIT	0.000	0.000	0.000	0.503	0.000	3.041	1.063	35,460
BIG4	0.000	1.000	1.000	0.751	1.000	1.000	0.432	35,460
ANA	0.000	0.000	0.693	0.953	1.833	2.843	1.034	35,460
INST	0.000	0.000	0.202	0.332	0.645	0.954	0.350	35,460
ILLIQ	0.000	0.000	0.000	0.041	0.000	0.072	0.235	35,460
MV	1.340	3.615	5.380	5.338	6.987	9.446	2.428	35,460
HHI	0.065	0.117	0.186	0.245	0.304	0.623	0.186	35,460
HHISQ	0.004	0.014	0.035	0.094	0.092	0.388	0.161	35,460
RD	0.000	0.000	0.004	0.070	0.078	0.337	0.150	35,460
ROA	-0.736	-0.020	0.093	-0.045	0.157	0.274	0.554	35,460
PPE	0.019	0.071	0.171	0.252	0.369	0.760	0.231	35,460
LEV	0.000	0.013	0.170	0.264	0.352	0.757	0.412	35,460
CAPEX	0.003	0.015	0.032	0.054	0.065	0.186	0.065	35,460
Q	0.753	1.108	1.551	2.553	2.501	6.969	3.592	35,460
KZ	-44.572	-6.082	-0.935	-7.909	1.120	7.097	35.058	35,460
AGE	1.386	2.079	2.565	2.607	3.091	3.871	0.720	35,460

Panel B: Number and Percentage of Firms with and without Patents by Industry

Industry Name	Description	Firms with Zero Patents		Firms with Positive Patents		No. of Firms
		No.	%	No.	%	No.
NoDur	Consumer nondurables (food, tobacco, textiles, apparel, leather, toys)	328	80%	83	20%	411
Durbl	Consumer durables (cars, TVs, furniture, household appliances)	117	56%	93	44%	210
Manuf	Manufacturing (machinery, trucks, planes, office furniture, paper, commercial printing)	485	59%	343	41%	828
Enrgy	Oil, gas, and coal extraction and products	377	88%	52	12%	429
Chems	Chemicals and allied products	132	64%	75	36%	207
BusEq	Business equipment (computers, software, and electronic equipment)	1,234	62%	748	38%	1,982
Telcm	Telephone and television transmission	314	86%	51	14%	365
Shops	Wholesale, retail, and some services (laundries, repair shops)	704	91%	66	9%	770
Hlth	Healthcare, medical equipment, and drugs	549	54%	472	46%	1,021
Other	Mines, construction, building materials, transportation, hotels, business services, entertainment	1,121	89%	138	11%	1,259
	Total	5,174	72%	2,121	28%	7,482

Table 2: Baseline Regressions - OLS Specifications

This table documents the regressions of firm innovation on audit quality. Panels A and B present the pooled OLS and firm fixed effects regressions, respectively. Both panels show the dependent variable as column heading and the key independent variable is audit quality ($BIG4$). Panel C reports the coefficient estimates on $BIG4$ for each of the Fama-French 12 industry groups based on the pooled OLS regressions. In all panels, detailed variable definitions are provided in Appendix A. Standard errors of the coefficient estimates are clustered by firm and displayed in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Pooled OLS

	(1)	(2)	(3)	(4)	(5)	(6)
	PAT_{t+1}	PAT_{t+2}	PAT_{t+3}	CIT_{t+1}	CIT_{t+2}	CIT_{t+3}
BIG4	-0.139***	-0.157***	-0.167***	-0.136***	-0.154***	-0.161***
	(0.018)	(0.020)	(0.022)	(0.019)	(0.020)	(0.022)
ANA	0.205***	0.198***	0.198***	0.211***	0.203***	0.201***
	(0.022)	(0.023)	(0.024)	(0.022)	(0.023)	(0.024)
INST	-0.383***	-0.380***	-0.391***	-0.376***	-0.376***	-0.386***
	(0.055)	(0.059)	(0.063)	(0.056)	(0.059)	(0.063)
ILLIQ	0.182***	0.125***	0.083***	0.168***	0.125***	0.078***
	(0.025)	(0.024)	(0.024)	(0.027)	(0.027)	(0.026)
HHI	-0.577***	-0.591***	-0.593**	-0.582***	-0.558**	-0.557**
	(0.216)	(0.226)	(0.236)	(0.222)	(0.233)	(0.242)
HHISQ	0.606**	0.638**	0.645**	0.605**	0.600**	0.607**
	(0.243)	(0.257)	(0.270)	(0.248)	(0.262)	(0.275)
MV	0.185***	0.189***	0.187***	0.183***	0.187***	0.185***
	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)	(0.010)
RD	0.326***	0.346***	0.339***	0.343***	0.359***	0.345***
	(0.054)	(0.060)	(0.065)	(0.056)	(0.061)	(0.067)
ROA	-0.046***	-0.039**	-0.040*	-0.043**	-0.036*	-0.037*
	(0.017)	(0.019)	(0.021)	(0.017)	(0.019)	(0.021)
PPE	-0.295***	-0.302***	-0.295***	-0.306***	-0.312***	-0.298***
	(0.061)	(0.065)	(0.069)	(0.062)	(0.066)	(0.069)
LEV	0.094***	0.090***	0.086***	0.089***	0.088***	0.083***
	(0.019)	(0.021)	(0.023)	(0.019)	(0.021)	(0.024)
CAPEX	0.339***	0.353***	0.389***	0.370***	0.396***	0.413***
	(0.113)	(0.124)	(0.140)	(0.116)	(0.129)	(0.143)
Q	-0.014***	-0.013***	-0.012***	-0.013***	-0.012***	-0.012***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
KZ	0.000***	0.000**	0.000*	0.000***	0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AGE	0.101***	0.096***	0.091***	0.094***	0.088***	0.083***
	(0.019)	(0.019)	(0.020)	(0.019)	(0.020)	(0.020)
INTERCEPT	-0.434***	-0.435***	-0.433***	-0.411***	-0.416***	-0.408***
	(0.065)	(0.068)	(0.071)	(0.066)	(0.069)	(0.072)
Industry fixed effects	Included	Included	Included	Included	Included	Included
Year fixed effects	Included	Included	Included	Included	Included	Included
Adjusted R^2	0.341	0.342	0.340	0.329	0.330	0.329
Obs.	35,460	28,855	23,094	35,460	28,855	23,094

Panel B: Firm Fixed Effects						
	(1)	(2)	(3)	(4)	(5)	(6)
	PAT_{t+1}	PAT_{t+2}	PAT_{t+3}	CIT_{t+1}	CIT_{t+2}	CIT_{t+3}
BIG4	-0.121***	-0.143***	-0.141***	-0.121***	-0.142***	-0.137***
	(0.017)	(0.017)	(0.021)	(0.017)	(0.018)	(0.022)
ANA	0.009	-0.010	-0.023	0.008	-0.008	-0.022
	(0.015)	(0.016)	(0.017)	(0.015)	(0.017)	(0.018)
INST	-0.102***	-0.083*	-0.104**	-0.118***	-0.114**	-0.138**
	(0.038)	(0.043)	(0.052)	(0.041)	(0.047)	(0.056)
ILLIQ	0.033*	0.016	0.004	0.015	0.021	-0.001
	(0.018)	(0.017)	(0.020)	(0.019)	(0.018)	(0.021)
HHI	0.519**	0.656***	0.824***	0.535**	0.684***	0.814***
	(0.211)	(0.231)	(0.261)	(0.218)	(0.240)	(0.267)
HHISQ	-0.490**	-0.631***	-0.822***	-0.530**	-0.684***	-0.860***
	(0.221)	(0.245)	(0.278)	(0.226)	(0.248)	(0.277)
MV	0.044***	0.051***	0.057***	0.046***	0.053***	0.057***
	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)	(0.008)
RD	-0.053	0.001	0.048	-0.027	0.028	0.032
	(0.047)	(0.055)	(0.064)	(0.051)	(0.058)	(0.070)
ROA	-0.012	-0.008	-0.021	-0.016	-0.008	-0.024*
	(0.010)	(0.012)	(0.013)	(0.011)	(0.013)	(0.014)
PPE	0.068	0.059	0.041	0.055	0.039	0.033
	(0.050)	(0.056)	(0.065)	(0.053)	(0.058)	(0.068)
LEV	-0.006	-0.005	-0.004	-0.009	-0.007	-0.006
	(0.013)	(0.015)	(0.018)	(0.015)	(0.017)	(0.019)
CAPEX	0.274***	0.193***	0.131	0.287***	0.228***	0.135
	(0.067)	(0.072)	(0.106)	(0.074)	(0.081)	(0.109)
Q	0.001	0.001	-0.001	0.001	0.000	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
KZ	-0.000	-0.000**	-0.000**	-0.000	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AGE	0.229***	0.237***	0.265***	0.210***	0.208***	0.229***
	(0.053)	(0.062)	(0.072)	(0.056)	(0.064)	(0.075)
INTERCEPT	-0.079	-0.124	-0.234	-0.041	-0.059	-0.131
	(0.129)	(0.151)	(0.180)	(0.136)	(0.158)	(0.189)
Firm fixed effects	Included	Included	Included	Included	Included	Included
Year fixed effects	Included	Included	Included	Included	Included	Included
Adjusted R^2	0.819	0.818	0.814	0.799	0.800	0.799
Obs.	35,460	28,855	23,094	35,460	28,855	23,094

Industry Name	Description	PAT_{t+1}	CIT_{t+1}	Obs.
NoDur	Consumer nondurables (food, tobacco, textiles, apparel, leather, toys)	-0.093** (0.043)	-0.090** (0.039)	2,131
Durbl	Consumer durables (cars, TVs, furniture, household appliances)	-0.216** (0.101)	-0.214* (0.117)	1,027
Manuf	Manufacturing (machinery, trucks, planes, office furniture, paper, commercial printing)	-0.261*** (0.063)	-0.241*** (0.066)	4,243
Enrgy	Oil, gas, and coal extraction and products	-0.065** (0.032)	-0.059* (0.032)	1,894
Chems	Chemicals and allied products	-0.254* (0.150)	-0.274* (0.150)	1,074
BusEq	Business equipment (computers, software, and electronic equipment)	-0.171*** (0.034)	-0.178*** (0.037)	9,282
Telcm	Telephone and television transmission	-0.037 (0.043)	-0.024 (0.045)	1,583
Shops	Wholesale, retail, and some services (laundries, repair shops)	-0.023* (0.013)	-0.015 (0.017)	3,784
Hlth	Healthcare, medical equipment, and drugs	-0.200*** (0.042)	-0.226*** (0.042)	4,977
Other	Mines, construction, building materials, hotels, transportation, business services, entertainment	-0.015 (0.026)	-0.018 (0.024)	5,465

Table 3: Baseline regressions - Changes in audit quality and change in firm innovation

This table displays the regressions of the change in firm innovation on the change in audit quality. In the table, ΔPAT (ΔCIT) is the change in a firm's patent counts (patent citations) for the years before and after its auditor switch. Dummy variable UP equals 1 if a firm changes from a non-Big 4 to Big 4 auditor in a fiscal year and 0 otherwise, DN equals 1 if a firm changes from a Big 4 to non-Big 4 auditor and 0 otherwise, $\Delta BIG4$ equals 1 if a firm changes from a Big 4 auditor to another Big 4 auditor and 0 otherwise, and $\Delta NBIG4$ equals 1 if a firm changes from a non-Big 4 auditor to another non-Big 4 auditor and 0 otherwise. For other explanatory variables, ΔX represents the change in variable X for the years before and after the auditor switch. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) ΔPAT	(2) ΔCIT
UP	0.071	0.061
	(0.050)	(0.057)
DN	0.064***	0.062**
	(0.022)	(0.025)
ΔBIG4	-0.029	-0.019
	(0.020)	(0.023)
ΔNBIG4	0.064***	0.063***
	(0.018)	(0.020)
ΔRD	0.028	0.028
	(0.037)	(0.042)
ΔMV	0.017***	0.019***
	(0.004)	(0.005)
ΔCAPEX	0.046	0.088
	(0.059)	(0.067)
ΔANA	0.016*	0.019*
	(0.009)	(0.010)
ΔINST	0.025	-0.008
	(0.026)	(0.030)
ΔILLIQ	0.472***	0.472***
	(0.014)	(0.016)
ΔPPE	-0.044	-0.032
	(0.040)	(0.046)
ΔLEV	-0.002	-0.002
	(0.011)	(0.013)
ΔROA	-0.005	-0.005
	(0.010)	(0.011)
ΔKZ	0.000	0.000
	(0.000)	(0.000)
ΔQ	-0.000	0.000
	(0.001)	(0.002)
ΔHHI	-0.209	-0.172
	(0.155)	(0.177)
ΔHHISQ	0.221	0.163
	(0.154)	(0.176)
ΔAGE	0.245***	0.209***
	(0.040)	(0.046)
INTERCEPT	-0.101***	-0.099***
	(0.005)	(0.005)
Adjusted R^2	0.047	0.037
Obs.	25,580	25,580

Table 4: Endogeneity tests – Quasi-natural Experiment of Enron/Andersen Collapse

This table reports the results of DiD tests on how an exogenous shock to audit quality due to 2002 Enron/Andersen collapse affects firm innovation. Sample selection begins with all firms with non-missing variables and observation outcomes before and after the shock (2002). Probit models in Panel A estimate the propensity scores for the treatment and control groups in the year prior to the Andersen collapse (2002). Treatment firms are Andersen's clients that change to non-Big 4 auditor after the collapse. Control firms are non-Andersen's clients that are audited by Big 4 auditors before the collapse. Each treatment firm is then matched to five control firms using the nearest neighbor propensity score matching procedure on a vector of observable characteristics including the variables in the baseline regression, and growth in innovation variables (PAT_GROWTH and CIT_GROWTH) before 2002. The dependent variable is 1 if firm-year belongs to treatment group, and 0 otherwise. The univariate comparisons between the treatment and control firms' characteristics and their corresponding t-statistics are documented in Panel B. DiD test results are shown in Panel C, where dummy variable $TREAT$ equals 1 for treatment firms and 0 for control firms, and $POST$ equals 1 if the fiscal year is after 2002 or 0 otherwise. The standard errors of estimated coefficients are clustered by firm and displayed in parentheses. ***, ** and * indicate the significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Pre-Match Propensity Score and Post-Match Diagnostic Regressions

	(1) Pre-Match	(2) Post-Match
ANA	-0.690	-0.030
	(0.494)	(0.705)
INST	-1.531	-1.371
	(1.369)	(1.768)
ILLIQ	-23.823	490.839**
	(22.868)	(215.264)
HHI	-8.493*	-14.278*
	(4.562)	(7.604)
HHISQ	7.067	12.643*
	(4.346)	(6.906)
MV	-0.490**	-0.641*
	(0.201)	(0.374)
RD	-7.195**	-10.131**
	(3.035)	(4.759)
ROA	-0.204	-0.422
	(0.852)	(1.496)
PPE	-0.031	-0.839
	(1.438)	(2.025)
LEV	0.268	1.963
	(1.069)	(1.399)
CAPEX	4.417	2.113
	(3.525)	(4.829)
Q	0.245	0.392
	(0.162)	(0.328)
KZ	-0.011	-0.014
	(0.011)	(0.012)
AGE	0.007	-0.338
	(0.325)	(0.437)
PAT_GROWTH	2.129**	-0.271
	(0.996)	(1.593)
CIT_GROWTH	0.094	0.914
	(0.323)	(0.611)
INTERCEPT	3.263*	3.993
	(1.973)	(3.037)
Industry Fixed Effects	Included	Included
Pseudo-R^2	0.469	0.330
p-value of χ^2	<0.001	0.524
Obs.	118	53

Panel B: Differences in Firm Characteristics				
	Treatment	Control	Differences	t-stat
ANA	0.250	0.227	0.023	0.18
INST	0.095	0.150	-0.055	-0.96
ILLIQ	0.001	0.000	0.001	1.57
HHI	0.244	0.347	-0.102	-1.41
HHI^2	0.096	0.200	-0.104	-1.36
MV	3.584	3.559	0.025	0.06
RD	0.087	0.067	0.020	0.54
ROA	-0.103	-0.026	-0.077	-0.84
PPE	0.255	0.233	0.022	0.34
LEV	0.181	0.161	0.020	0.33
CAPEX	0.063	0.041	0.022	1.00
Q	2.180	1.596	0.584	0.74
KZ	-18.054	-1.293	-16.761	-1.39
AGE	2.481	2.575	-0.094	-0.49
PAT_GROWTH	-0.663	-0.823	0.160	1.67
CIT_GROWTH	-0.721	-0.830	0.109	0.99

Panel C: Difference-in-Difference Tests						
	(1)	(2)	(3)	(4)	(5)	(6)
	PAT_{t+1}	PAT_{t+2}	PAT_{t+3}	CIT_{t+1}	CIT_{t+2}	CIT_{t+3}
TREAT*POST	0.135**	0.143**	0.153**	0.097*	0.127**	0.122**
	(0.063)	(0.064)	(0.059)	(0.056)	(0.061)	(0.059)
ANA	-0.070	-0.027	-0.058	-0.039	-0.001	-0.039
	(0.060)	(0.050)	(0.061)	(0.063)	(0.053)	(0.059)
INST	0.127	0.168	0.179	-0.017	0.066	0.112
	(0.176)	(0.189)	(0.226)	(0.150)	(0.142)	(0.188)
ILLIQ	-0.133***	-0.035	-0.013	-0.156***	-0.082	-0.068
	(0.049)	(0.059)	(0.065)	(0.054)	(0.069)	(0.072)
HHI	-0.723	-0.597	-0.425	-0.419	-0.310	-0.178
	(0.573)	(0.470)	(0.441)	(0.551)	(0.513)	(0.493)
HHISQ	0.207	0.177	0.018	0.002	-0.016	-0.182
	(0.455)	(0.385)	(0.372)	(0.435)	(0.422)	(0.429)
MV	0.135**	0.092**	0.105**	0.128**	0.088**	0.098*
	(0.057)	(0.037)	(0.047)	(0.053)	(0.037)	(0.050)
RD	0.087	0.047	0.182	0.083	0.101	0.226
	(0.296)	(0.227)	(0.297)	(0.265)	(0.229)	(0.315)
ROA	-0.116	-0.036	-0.065	-0.097	0.050	-0.054
	(0.078)	(0.085)	(0.116)	(0.083)	(0.083)	(0.150)
PPE	0.121	0.082	0.217	0.058	-0.141	-0.009
	(0.166)	(0.171)	(0.204)	(0.142)	(0.173)	(0.172)
LEV	0.028	-0.009	0.015	0.011	0.001	0.021
	(0.057)	(0.051)	(0.091)	(0.049)	(0.059)	(0.085)
CAPEX	-0.124	0.005	-0.326	0.025	0.383	-0.376
	(0.275)	(0.280)	(0.355)	(0.311)	(0.454)	(0.378)
Q	0.009	0.011	-0.006	0.018	0.018	0.008
	(0.018)	(0.015)	(0.015)	(0.020)	(0.016)	(0.021)
KZ	-0.000	-0.000	0.000	-0.001	-0.001	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
AGE	0.049	0.002	0.009	0.033	-0.012	0.005
	(0.076)	(0.058)	(0.066)	(0.072)	(0.057)	(0.069)
INTERCEPT	-0.307	-0.133	-0.229	-0.325	-0.133	-0.197
	(0.255)	(0.238)	(0.244)	(0.245)	(0.242)	(0.279)
Industry fixed effects	Included	Included	Included	Included	Included	Included
Year fixed effects	Included	Included	Included	Included	Included	Included
Adjusted R^2	0.301	0.266	0.249	0.236	0.198	0.172
Obs.	397	343	289	397	343	289

Table 5: Endogeneity tests – Heckman Selection Model

This table reports the outcome of the Heckman two-stage estimation approach. In the untabulated first stage, $BIG4$ is estimated using a Probit regression that employs total asset turnover $TATURN$, research and development dummy RDD, total assets growth TAG, ratio of current assets to total assets CA, in addition to all the control variables used in Table 2. We then use the fitted value of $BIG4$ from the first stage regression (*Predicted_BIG4*) and also add the inverse Mills ratio (IMR) in our baseline OLS regression in the second-stage regression. The standard errors of estimated coefficients are clustered by firm and displayed in parentheses. ***, ** and * indicate the significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	PAT_{t+1}	PAT_{t+2}	PAT_{t+3}	CIT_{t+1}	CIT_{t+2}	CIT_{t+3}
Predicted_BIG4	-0.083***	-0.099***	-0.113***	-0.081***	-0.099***	-0.105***
	(0.019)	(0.020)	(0.026)	(0.020)	(0.022)	(0.029)
IMR	0.126***	0.149***	0.160***	0.127***	0.148***	0.162***
	(0.008)	(0.011)	(0.014)	(0.009)	(0.011)	(0.014)
ANA	0.020	-0.019	-0.028	0.020	-0.020	-0.032
	(0.021)	(0.024)	(0.027)	(0.021)	(0.024)	(0.027)
INST	0.048	0.085	0.055	0.032	0.067	0.050
	(0.047)	(0.058)	(0.072)	(0.050)	(0.060)	(0.075)
ILLIQ	-0.008	0.011	-0.001	-0.024	0.023	-0.013
	(0.025)	(0.024)	(0.027)	(0.027)	(0.028)	(0.029)
HHI	0.562**	0.684**	0.666*	0.600**	0.810**	0.762*
	(0.284)	(0.323)	(0.390)	(0.292)	(0.331)	(0.406)
HHISQ	-0.633**	-0.798**	-0.842**	-0.697**	-0.944***	-0.998**
	(0.291)	(0.332)	(0.404)	(0.298)	(0.336)	(0.414)
MV	0.032***	0.043***	0.048***	0.033***	0.043***	0.046***
	(0.009)	(0.011)	(0.012)	(0.010)	(0.011)	(0.012)
RD	-0.095	0.035	0.179*	-0.022	0.066	0.156
	(0.071)	(0.077)	(0.100)	(0.076)	(0.081)	(0.100)
ROA	-0.036**	-0.051***	-0.076***	-0.039**	-0.047**	-0.072***
	(0.015)	(0.019)	(0.024)	(0.016)	(0.020)	(0.024)
PPE	0.199***	0.166**	0.086	0.183***	0.162*	0.090
	(0.067)	(0.084)	(0.106)	(0.069)	(0.088)	(0.110)
LEV	-0.016	-0.022	0.006	-0.017	-0.022	0.010
	(0.018)	(0.024)	(0.027)	(0.019)	(0.025)	(0.029)
CAPEX	0.310***	0.270**	0.210	0.323***	0.282**	0.228
	(0.103)	(0.113)	(0.176)	(0.106)	(0.119)	(0.175)
Q	-0.003	-0.005	-0.009**	-0.003	-0.005	-0.008*
	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)	(0.004)
KZ	-0.000	0.000	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AGE	0.352***	0.413***	0.525***	0.302***	0.382***	0.474***
	(0.102)	(0.124)	(0.157)	(0.106)	(0.128)	(0.162)
INTERCEPT	-0.506*	-1.577***	-1.807***	-0.376	-1.494***	-1.658***
	(0.272)	(0.383)	(0.481)	(0.282)	(0.395)	(0.496)
Firm fixed effects	Included	Included	Included	Included	Included	Included
Year fixed effects	Included	Included	Included	Included	Included	Included
Adjusted R^2	0.817	0.809	0.798	0.801	0.797	0.787
Obs.	23,094	18,005	13,543	23,094	18,005	13,543

Table 6: Alternative Measures of Audit Quality

This table presents the re-estimation of our baseline regressions using alternative proxies of audit quality. Panel A adopts $AUDIT\_FEE$ for audit quality, which is the natural logarithm of audit fees. Panel B adopts $SPEC$ for audit quality, where the $SPEC$ of firm *i* in industry *j* is measured as the sales of all firms in industry *j* that are audited by the same auditor of firm's scaled by the sales for all firms in industry *j*. Panel C adopts GC for audit quality, which equals 1 if a firm's auditor issues going concern opinion and 0 otherwise. The standard errors of estimated coefficients are clustered by firm and displayed in parentheses. ***, ** and * indicate the significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Audit Fee

	(1)	(2)	(3)	(4)	(5)	(6)
	PAT_{t+1}	PAT_{t+2}	PAT_{t+3}	CIT_{t+1}	CIT_{t+2}	CIT_{t+3}
AUDIT_FEE	-0.045***	-0.060***	-0.076***	-0.046***	-0.064***	-0.078***
	(0.009)	(0.010)	(0.011)	(0.010)	(0.011)	(0.012)
ANA	0.010	-0.008	-0.020	0.010	-0.005	-0.019
	(0.015)	(0.016)	(0.017)	(0.016)	(0.017)	(0.018)
INST	-0.100***	-0.075*	-0.089*	-0.116***	-0.106**	-0.121**
	(0.038)	(0.043)	(0.052)	(0.041)	(0.047)	(0.056)
ILLIQ	0.029	0.013	0.001	0.011	0.017	-0.003
	(0.018)	(0.017)	(0.020)	(0.020)	(0.018)	(0.021)
HHI	0.516**	0.644***	0.806***	0.531**	0.670***	0.796***
	(0.211)	(0.232)	(0.260)	(0.219)	(0.240)	(0.267)
HHISQ	-0.490**	-0.627**	-0.819***	-0.530**	-0.680***	-0.857***
	(0.221)	(0.245)	(0.276)	(0.226)	(0.248)	(0.275)
MV	0.047***	0.055***	0.061***	0.049***	0.057***	0.061***
	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)	(0.008)
RD	-0.061	-0.012	0.029	-0.035	0.014	0.013
	(0.047)	(0.054)	(0.063)	(0.051)	(0.057)	(0.069)
ROA	-0.015	-0.011	-0.026**	-0.019*	-0.012	-0.030**
	(0.010)	(0.012)	(0.013)	(0.011)	(0.012)	(0.014)
PPE	0.065	0.060	0.044	0.053	0.041	0.037
	(0.049)	(0.056)	(0.065)	(0.052)	(0.058)	(0.067)
LEV	-0.000	0.003	0.006	-0.003	0.001	0.004
	(0.013)	(0.015)	(0.018)	(0.014)	(0.017)	(0.019)
CAPEX	0.263***	0.176**	0.117	0.274***	0.208***	0.119
	(0.068)	(0.072)	(0.106)	(0.075)	(0.081)	(0.109)
Q	0.000	-0.001	-0.003	0.000	-0.001	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
KZ	-0.000	-0.000*	-0.000**	-0.000	-0.000*	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AGE	0.236***	0.244***	0.271***	0.217***	0.214***	0.235***
	(0.054)	(0.062)	(0.072)	(0.056)	(0.065)	(0.075)
INTERCEPT	0.330*	0.456**	0.536**	0.388**	0.567***	0.668***
	(0.178)	(0.202)	(0.232)	(0.188)	(0.213)	(0.244)
Firm fixed effects	Included	Included	Included	Included	Included	Included
Year fixed effects	Included	Included	Included	Included	Included	Included
Adjusted R^2	0.819	0.818	0.814	0.799	0.800	0.799
Obs.	35,460	28,855	23,094	35,460	28,855	23,094

Panel B: Industry Specialist						
	(1)	(2)	(3)	(4)	(5)	(6)
	PAT_{t+1}	PAT_{t+2}	PAT_{t+3}	CIT_{t+1}	CIT_{t+2}	CIT_{t+3}
SPEC	-0.124***	-0.152***	-0.152***	-0.120***	-0.153***	-0.152***
	(0.043)	(0.043)	(0.046)	(0.045)	(0.045)	(0.048)
ANA	0.009	-0.009	-0.023	0.009	-0.007	-0.022
	(0.015)	(0.016)	(0.017)	(0.015)	(0.017)	(0.018)
INST	-0.112***	-0.094**	-0.117**	-0.128***	-0.126***	-0.150***
	(0.038)	(0.043)	(0.052)	(0.041)	(0.047)	(0.056)
ILLIQ	0.030*	0.013	0.002	0.012	0.018	-0.003
	(0.018)	(0.017)	(0.020)	(0.020)	(0.018)	(0.021)
HHI	0.524**	0.659***	0.829***	0.541**	0.686***	0.819***
	(0.211)	(0.232)	(0.261)	(0.219)	(0.240)	(0.267)
HHISQ	-0.487**	-0.628**	-0.824***	-0.527**	-0.681***	-0.862***
	(0.221)	(0.245)	(0.278)	(0.226)	(0.248)	(0.277)
MV	0.043***	0.051***	0.057***	0.045***	0.053***	0.057***
	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)	(0.008)
RD	-0.052	0.001	0.048	-0.025	0.028	0.032
	(0.047)	(0.055)	(0.064)	(0.051)	(0.058)	(0.070)
ROA	-0.011	-0.006	-0.020	-0.014	-0.006	-0.023*
	(0.010)	(0.012)	(0.013)	(0.011)	(0.013)	(0.014)
PPE	0.056	0.046	0.026	0.043	0.027	0.018
	(0.049)	(0.056)	(0.065)	(0.052)	(0.058)	(0.067)
LEV	-0.003	-0.000	0.001	-0.006	-0.002	-0.002
	(0.013)	(0.015)	(0.018)	(0.015)	(0.017)	(0.020)
CAPEX	0.283***	0.201***	0.142	0.295***	0.236***	0.145
	(0.067)	(0.072)	(0.106)	(0.074)	(0.081)	(0.109)
Q	0.002	0.001	-0.000	0.002	0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
KZ	-0.000*	-0.000**	-0.000***	-0.000*	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AGE	0.232***	0.240***	0.268***	0.213***	0.211***	0.231***
	(0.054)	(0.062)	(0.073)	(0.056)	(0.065)	(0.076)
INTERCEPT	-0.159	-0.218	-0.328*	-0.121	-0.154	-0.221
	(0.130)	(0.152)	(0.182)	(0.137)	(0.159)	(0.190)
Firm fixed effects	Included	Included	Included	Included	Included	Included
Year fixed effects	Included	Included	Included	Included	Included	Included
Adjusted R^2	0.819	0.817	0.814	0.799	0.799	0.798
Obs.	35,460	28,855	23,094	35,460	28,855	23,094

Panel C: Going Concern Opinion						
	(1)	(2)	(3)	(4)	(5)	(6)
	PAT_{t+1}	PAT_{t+2}	PAT_{t+3}	CIT_{t+1}	CIT_{t+2}	CIT_{t+3}
GC	0.174***	0.173***	0.184***	0.171***	0.170***	0.181***
	(0.022)	(0.025)	(0.027)	(0.022)	(0.025)	(0.027)
ANA	0.205***	0.200***	0.200***	0.211***	0.205***	0.204***
	(0.022)	(0.023)	(0.024)	(0.022)	(0.023)	(0.024)
INST	-0.404***	-0.407***	-0.420***	-0.397***	-0.402***	-0.413***
	(0.056)	(0.059)	(0.064)	(0.056)	(0.060)	(0.064)
ILLIQ	0.181***	0.122***	0.080***	0.166***	0.122***	0.075***
	(0.024)	(0.024)	(0.024)	(0.027)	(0.027)	(0.026)
HHI	-0.583***	-0.602***	-0.610***	-0.588***	-0.570**	-0.573**
	(0.216)	(0.227)	(0.236)	(0.222)	(0.233)	(0.242)
HHISQ	0.620**	0.658**	0.673**	0.619**	0.619**	0.634**
	(0.243)	(0.257)	(0.270)	(0.248)	(0.262)	(0.276)
MV	0.177***	0.179***	0.177***	0.176***	0.178***	0.176***
	(0.009)	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)
RD	0.269***	0.279***	0.269***	0.287***	0.294***	0.278***
	(0.054)	(0.059)	(0.065)	(0.056)	(0.061)	(0.066)
ROA	-0.017	-0.010	-0.008	-0.015	-0.007	-0.006
	(0.017)	(0.019)	(0.021)	(0.017)	(0.019)	(0.021)
PPE	-0.323***	-0.331***	-0.326***	-0.333***	-0.340***	-0.328***
	(0.061)	(0.065)	(0.069)	(0.062)	(0.066)	(0.070)
LEV	0.072***	0.071***	0.068***	0.067***	0.068***	0.066***
	(0.018)	(0.021)	(0.023)	(0.019)	(0.021)	(0.024)
CAPEX	0.404***	0.424***	0.460***	0.434***	0.465***	0.482***
	(0.112)	(0.124)	(0.139)	(0.116)	(0.128)	(0.142)
Q	-0.011***	-0.010***	-0.009***	-0.010***	-0.009***	-0.008***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
KZ	0.000**	0.000*	0.000	0.000**	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AGE	0.106***	0.101***	0.096***	0.098***	0.093***	0.088***
	(0.019)	(0.020)	(0.020)	(0.019)	(0.020)	(0.020)
INTERCEPT	-0.527***	-0.535***	-0.542***	-0.503***	-0.514***	-0.513***
	(0.068)	(0.071)	(0.074)	(0.069)	(0.072)	(0.075)
Industry fixed effects	Included	Included	Included	Included	Included	Included
Year fixed effects	Included	Included	Included	Included	Included	Included
Adjusted R^2	0.341	0.341	0.339	0.328	0.329	0.328
Obs.	35,460	28,855	23,094	35,460	28,855	23,094

Table 7: Different Subsamples

Panel A re-estimates the baseline model with a subsample of innovative firms that have at least one patent over the sample period. Panel B uses a subsample of non-Big 4 clients, where $LARGE\_NON\_BIG4$ equals 1 if firms have Grant Thornton, BDO Seidman, Crowe Chizek and McGladrey & Pullen as auditors and 0 otherwise. In Panel C, we restrict our sample to firms with minimum auditor tenure of five years and re-estimate the baseline model. The standard errors of estimated coefficients are clustered by firm and displayed in parentheses. ***, ** and * indicate the significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Subsample of Innovative Firms						
	(1)	(2)	(3)	(4)	(5)	(6)
	PAT_{t+1}	PAT_{t+2}	PAT_{t+3}	CIT_{t+1}	CIT_{t+2}	CIT_{t+3}
BIG4	-0.252***	-0.294***	-0.274***	-0.251***	-0.294***	-0.265***
	(0.037)	(0.038)	(0.048)	(0.040)	(0.042)	(0.051)
ANA	0.009	-0.010	-0.027	0.008	-0.005	-0.025
	(0.026)	(0.028)	(0.028)	(0.028)	(0.031)	(0.031)
INST	-0.009	0.045	0.025	-0.046	-0.026	-0.041
	(0.076)	(0.084)	(0.095)	(0.082)	(0.092)	(0.104)
ILLIQ	-0.077***	-0.110***	-0.117***	-0.096***	-0.104***	-0.121***
	(0.018)	(0.018)	(0.021)	(0.019)	(0.019)	(0.022)
HHI	0.372	0.258	0.430	0.410	0.334	0.384
	(0.472)	(0.508)	(0.561)	(0.497)	(0.534)	(0.589)
HHISQ	-0.496	-0.444	-0.660	-0.599	-0.584	-0.736
	(0.511)	(0.547)	(0.582)	(0.526)	(0.556)	(0.581)
MV	0.083***	0.053***	0.045**	0.088***	0.057***	0.046**
	(0.018)	(0.019)	(0.020)	(0.020)	(0.021)	(0.022)
RD	0.035	-0.033	-0.064	0.080	0.037	-0.110
	(0.113)	(0.129)	(0.138)	(0.128)	(0.146)	(0.154)
ROA	0.016	0.014	-0.048	-0.019	0.007	-0.061
	(0.053)	(0.055)	(0.056)	(0.057)	(0.062)	(0.062)
PPE	0.039	0.060	-0.012	-0.019	-0.019	-0.031
	(0.164)	(0.180)	(0.200)	(0.183)	(0.192)	(0.211)
LEV	-0.081	-0.080	-0.060	-0.098*	-0.091	-0.077
	(0.049)	(0.056)	(0.064)	(0.058)	(0.066)	(0.071)
CAPEX	0.707***	0.352	0.001	0.764***	0.495*	0.013
	(0.240)	(0.236)	(0.315)	(0.273)	(0.272)	(0.332)
Q	-0.004	0.002	0.000	-0.004	0.001	-0.001
	(0.005)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
KZ	-0.000	-0.001*	-0.001*	-0.000	-0.001*	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AGE	0.122	0.161	0.254**	0.087	0.107	0.180
	(0.098)	(0.108)	(0.124)	(0.106)	(0.117)	(0.132)
INTERCEPT	0.971***	1.084***	0.856**	1.038***	1.204***	1.088***
	(0.273)	(0.299)	(0.346)	(0.295)	(0.323)	(0.372)
Firm fixed effects	Included	Included	Included	Included	Included	Included
Year fixed effects	Included	Included	Included	Included	Included	Included
Adjusted R^2	0.817	0.820	0.821	0.792	0.797	0.801
Obs.	13,878	11,797	9,801	13,878	11,797	9,801

Panel B: Subsample of Non Big 4 auditors						
	(1)	(2)	(3)	(4)	(5)	(6)
	PAT_{t+1}	PAT_{t+2}	PAT_{t+3}	CIT_{t+1}	CIT_{t+2}	CIT_{t+3}
LARGE_NON_BIG4	0.050	0.038	-0.004	0.039	0.033	-0.001
	(0.027)	(0.028)	(0.027)	(0.027)	(0.029)	(0.021)
ANA	0.018	0.012	0.046	-0.001	0.004	0.040
	(0.026)	(0.022)	(0.032)	(0.022)	(0.019)	(0.029)
INST	-0.164*	-0.202**	-0.289*	-0.125	-0.140	-0.240
	(0.095)	(0.102)	(0.166)	(0.090)	(0.089)	(0.154)
ILLIQ	-0.016	0.012	-0.025	0.014	0.032	-0.009
	(0.045)	(0.040)	(0.043)	(0.043)	(0.035)	(0.038)
HHI	-0.158	-0.062	-0.051	-0.115	-0.117	-0.034
	(0.239)	(0.301)	(0.309)	(0.267)	(0.318)	(0.254)
HHISQ	0.039	-0.017	-0.010	0.000	0.041	-0.002
	(0.176)	(0.216)	(0.234)	(0.191)	(0.219)	(0.193)
MV	0.008	0.011*	0.002	0.006	0.010*	0.001
	(0.005)	(0.006)	(0.008)	(0.005)	(0.005)	(0.007)
RD	-0.002	0.029	0.017	-0.023	0.043	0.012
	(0.045)	(0.041)	(0.035)	(0.054)	(0.047)	(0.030)
ROA	-0.001	0.002	0.001	-0.000	0.000	0.003
	(0.004)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
PPE	-0.000	0.008	0.036	-0.013	-0.001	0.036
	(0.024)	(0.024)	(0.038)	(0.026)	(0.024)	(0.036)
LEV	0.002	0.002	-0.007	0.003	0.002	-0.009
	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)
CAPEX	0.118**	0.033	-0.176	0.152*	0.019	-0.157
	(0.057)	(0.047)	(0.151)	(0.082)	(0.048)	(0.138)
Q	0.000	0.001	0.001	0.001	0.000	0.001
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
KZ	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AGE	0.068	0.095*	0.095*	0.053	0.057	0.071
	(0.045)	(0.049)	(0.053)	(0.043)	(0.049)	(0.049)
INTERCEPT	-0.037	-0.110	-0.086	-0.003	-0.037	-0.053
	(0.083)	(0.101)	(0.096)	(0.074)	(0.109)	(0.081)
Firm fixed effects	Included	Included	Included	Included	Included	Included
Year fixed effects	Included	Included	Included	Included	Included	Included
Adjusted R^2	0.502	0.495	0.500	0.496	0.498	0.497
Obs.	5,742	4,344	3,244	5,742	4,344	3,244

Panel C: Subsample of Long Auditor Tenure						
	(1)	(2)	(3)	(4)	(5)	(6)
	PAT_{t+1}	PAT_{t+2}	PAT_{t+3}	CIT_{t+1}	CIT_{t+2}	CIT_{t+3}
BIG4	-0.208***	-0.239***	-0.243***	-0.206***	-0.234***	-0.240***
	(0.044)	(0.045)	(0.045)	(0.043)	(0.044)	(0.045)
ANA	0.174***	0.160***	0.155***	0.178***	0.162***	0.159***
	(0.032)	(0.031)	(0.031)	(0.031)	(0.030)	(0.031)
INST	-0.355***	-0.326***	-0.321***	-0.343***	-0.314***	-0.313***
	(0.082)	(0.082)	(0.084)	(0.080)	(0.081)	(0.082)
ILLIQ	0.204***	0.172***	0.114***	0.184***	0.171***	0.107***
	(0.050)	(0.042)	(0.038)	(0.057)	(0.049)	(0.041)
HHI	0.987**	1.019*	0.906	0.941**	1.008*	0.776
	(0.439)	(0.530)	(0.655)	(0.449)	(0.535)	(0.648)
HHISQ	-1.029**	-1.146**	-1.170**	-1.011**	-1.161**	-1.078*
	(0.411)	(0.485)	(0.591)	(0.415)	(0.486)	(0.582)
MV	0.233***	0.233***	0.225***	0.232***	0.232***	0.223***
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
RD	0.480***	0.394**	0.332*	0.497***	0.415***	0.340**
	(0.156)	(0.155)	(0.177)	(0.151)	(0.146)	(0.170)
ROA	-0.013	-0.012	-0.017	-0.018	-0.011	-0.012
	(0.047)	(0.046)	(0.045)	(0.049)	(0.046)	(0.046)
PPE	-0.326**	-0.300**	-0.266*	-0.350**	-0.310**	-0.267*
	(0.145)	(0.148)	(0.154)	(0.143)	(0.147)	(0.152)
LEV	0.141***	0.132***	0.135***	0.141***	0.133***	0.139***
	(0.044)	(0.045)	(0.044)	(0.046)	(0.047)	(0.046)
CAPEX	0.593**	0.564**	0.528**	0.611**	0.581**	0.543**
	(0.247)	(0.244)	(0.254)	(0.250)	(0.247)	(0.253)
Q	-0.016**	-0.013*	-0.010	-0.016**	-0.013*	-0.009
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
KZ	0.001**	0.001**	0.000*	0.001**	0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AGE	0.116***	0.110***	0.105***	0.103***	0.099***	0.094***
	(0.032)	(0.031)	(0.031)	(0.032)	(0.031)	(0.030)
INTERCEPT	-0.793***	-0.770***	-0.744***	-0.748***	-0.734***	-0.678***
	(0.207)	(0.208)	(0.213)	(0.204)	(0.203)	(0.206)
Firm fixed effects	Included	Included	Included	Included	Included	Included
Year fixed effects	Included	Included	Included	Included	Included	Included
Adjusted R^2	0.458	0.453	0.444	0.447	0.443	0.436
Obs.	19,612	16,875	14,059	19,612	16,875	14,059

Table 8: Economic Mechanism – Analyst Coverage

This table presents the tests on the possible channels through which audit quality affects firm innovation: analyst coverage. Column (1) applies the pooled OLS analysis to the whole sample, while Column (2) shows the effect of an exogenous shock to audit quality on analyst coverage using the DiD sample. Variables definitions are provided in Appendix A. The standard errors of estimated coefficients are clustered by firm and displayed in parentheses. ***, ** and * indicate the significance at the 1%, 5%, and 10% levels, respectively.

	(1) ANA_{t+1}	(2) ANA_{t+1}
BIG4	0.066***	
	(0.017)	
TREAT*POST		-0.395***
		(0.141)
ROA	0.004	0.104
	(0.010)	(0.142)
CAPEX	0.391***	-0.459
	(0.121)	(1.267)
RD	0.102**	0.341
	(0.045)	(0.385)
ADVER	-0.017	1.622
	(0.246)	(3.838)
MV	0.135***	0.220***
	(0.007)	(0.055)
LEV	0.105***	0.372*
	(0.014)	(0.192)
TRADE	0.086***	0.025
	(0.003)	(0.017)
SD	-0.977***	-0.173
	(0.055)	(0.134)
RECIP_P	-0.445***	-0.107
	(0.017)	(0.081)
SP_500	0.487***	0.000
	(0.048)	(.)
SH_BASE	-0.014**	-0.035
	(0.005)	(0.054)
INTERCEPT	-0.546***	-0.697***
	(0.025)	(0.192)
Industry fixed effects	Included	Included
Year fixed effects	Included	Included
Adjusted R^2	0.549	0.412
Obs.	35,460	397

Table 9: Economic Mechanism – Non-dedicated Institutional Investors

This table presents the tests on the possible channels through which audit quality affects firm innovation: non-dedicated investor holdings, NON_DED. Column (1) applies the pooled OLS analysis to the whole sample, while Column (2) shows the effect of an exogenous shock to audit quality on non-dedicated investor holdings using the DiD sample. Variables definitions are provided in Appendix A. The standard errors of estimated coefficients are clustered by firm and displayed in parentheses. ***, ** and * indicate the significance at the 1%, 5%, and 10% levels, respectively.

	(1) NON_DED_{t+1}	(2) NON_DED_{t+1}
BIG4	0.074***	
	(0.007)	
TREAT*POST		-0.098**
		(0.041)
LEV	0.016***	-0.091
	(0.005)	(0.063)
MV	0.030***	0.096***
	(0.002)	(0.012)
Q	0.002***	-0.022***
	(0.001)	(0.003)
SP_500	0.020	0.000
	(0.015)	(.)
ILLIQ	-0.058***	-0.020
	(0.006)	(0.022)
RD	-0.135***	-0.048
	(0.015)	(0.099)
RETURN	0.025***	0.009
	(0.008)	(0.032)
LN_TRADE	0.019***	-0.001
	(0.001)	(0.003)
AGE	0.037***	0.015
	(0.005)	(0.024)
INTERCEPT	-0.263***	-0.233***
	(0.012)	(0.084)
Industry fixed effects	Included	Included
Year fixed effects	Included	Included
Adjusted R^2	0.410	0.640
Obs.	35,460	397