Asset Impairments and Innovation: Evidence from Regression Kink Design

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October 2019

We thank Kulwant Singh, Weinjie Xue, Seil Kim, and workshop participants at Washington University in St. Louis, Peking University, and PKU-NTU Joint Symposium for helpful comments. We thank financial supports from Guanghua School of Management and NUS Business School. All errors are our own.

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Abstract

We examine whether accounting regulation of asset impairments affects a firm's innovation. To identify causal effects, we use the regression kink design (RKD) and exploit exogenous variation of the asset impairment loss recognition instituted by SFAS 142 and 144. Focusing on a narrow window around a cutoff point at which Book-To-Market (BTM) equals 1, we find that the sensitivity of the asset impairments to BTM increases at the cutoff point. We provide evidence that increased exposure to asset impairments leads to an increase in R&D and capital expenditures. Such effects are more pronounced for firms having greater access to external financing, younger firms, and firms with lower sales growth relative to their industry sales growth. We also find that the effects of the accounting regulation are stronger when audit quality is higher. Further evidence reveals that increased exposure to asset impairments leads to more patent filings with increased citations per patent but a decrease in M&A activities, suggesting that those firms change growth policies from external acquisitions to internal development. Overall, our findings suggest that accounting regulation of asset impairments shapes the process of seeking new growth engines for the firm.

Keywords: Asset impairments; SFAS 142; SFAS 144; Growth strategy; Innovation; R&D; M&A

JEL classifications: M41, M42, G34, O31, O32

1. Introduction

We investigate whether the accounting regulation of impairments affects a firm's investment in innovation. A growing literature suggests that accounting has real effects on a firm's investment.[1] Even though financial accounting for asset impairments has received significant attention in accounting literature (e.g., Alciatore et al. 1998; Riedl 2004; Lawrence et al. 2013), whether it affects a firm's real investment remains largely unexplored. This is indeed an important gap in the literature because "the reporting of asset impairments is conceptually a function of economic factors and reporting incentives" (Riedl 2004). Most prior studies that examine the effects of asset impairment threats assume exogenous economic factors and investigate whether managers use discretion to report opportunistically in the hope that the economic conditions will improve.[2] In our paper, we fill this gap by providing evidence that the asset impairment threats prompt managers to invest in internal innovation activities, improving the economic fundamentals of the firm.

Literature in organizational economics suggests that trial-and-error learning in an organization is a critical process that drives the success of the organization: actions associated with positive outcomes can be repeated, but actions associated with negative outcomes will be avoided (Cyert and March 1963; Levinthal and March 1981). In such a process, corporate boards engage in a series of interactive actions such as information gathering to understand the effectiveness of prior actions and influence future actions proactively (Koberg 1987). However, managers lack incentives to voluntarily share such information due to agency frictions and career concerns,

[1] Prior research primarily argues that accounting information with high quality reduces the cost of capital, facilitating external financing and thus affecting investment (e.g., McNichos and Stubben 2008, Biddle et al. 2009, Lara et al. 2016, Shroff 2017, Christensen et al. 2017, and Zhong 2018).
[2] For example, see Francis et al. (1996), Riedl (2004), Beatty and Weber (2006), Hayn and Hughes (2006), Ramanna (2008), Ramanna and Watts (2012), and Li and Sloan (2017).

especially when firm performance deteriorates (e.g., Berger and Hann 2007; Kothari et al. 2008; Armstrong et al. 2010).[3] Moreover, organization inertia discourages managers from proactively engaging in strategic changes in response to declining firm performance (Hannan and Feeman 1977). Hence, it is essential to understand what organizational and institutional mechanisms facilitate the organization's learning process and how they contribute to firm value.

Financial reporting and disclosures play a crucial role in the organization's learning process by reducing information asymmetry between the principals (e.g., shareholders and boards) and managers (Armstrong et al. 2010), especially when such disclosures are subject to SEC rules, enforcement, and the oversight of an auditor (Bushman et al. 2004). The accounting regulation of long-lived asset impairments requires managers to have periodic re-evaluations of the future cash flows generated from the current business models. If a firm's current technologies and business models are obsolete or the expected synergies from past M&A activities are no longer available, then the recoverable amount of the long-lived assets including goodwill would fall below the carrying value, and thereby the firm should consider recognizing asset impairment losses. In this regard, the accounting regulation of the asset impairments and its enforcement by auditors facilitate the trial-and-error learning process. First, the regulation forces firms to revise their expectations about the capabilities of existing assets to generate future cash flows. Second, the accounting report reveals the state of nature to the boards and other stakeholders with higher credibility (e.g., Bushman et al. 2004), allowing them to assess the effectiveness of prior actions.

[3] For example, Armstrong et al. (2010) state that "agency conflicts exist between managers and shareholders, and although managers will be forthcoming in sharing a considerable amount of information with outside directors, as discussed by Verrecchia (2001), they are less likely to voluntarily share information with outside directors that is detrimental to their own interests (e.g., information about bad projects, poor performance, perquisite consumption, and accounting irregularities)."

Hence, the accounting regulation of the long-lived asset impairments acts as an external governance mechanism and helps firms pivot the business models and growth strategies.

Our goal is to provide evidence on the effects of the increased threats of goodwill and long-lived asset impairments on a firm's investment strategies. The identification of the causal effects, however, is challenging because the increased threats of asset impairments (i.e., accounting treatment of the ex-post outcome), a decrease in firm value (i.e., economic fundamentals), and the changes in the firm's investment strategies are all endogenously determined. Furthermore, the realized asset impairments are correlated with and caused by unobservable factors including managerial manipulations (e.g., Riedl 2004; Beatty and Weber 2006; Ramanna and Watts 2012). Hence, the identification requires exogenous variations in the ex-ante threats of asset impairments holding other firm characteristics constant.

To address the identification issue, we rely on the accounting regulation of the asset impairments guided by SFAS 142 and SFAS 144, under which the enforcement of recognizing impairment losses exhibits a sharp increase when a firm's book-to-market ratio (BTM) exceeds 1 (Lawrence et al. 2013; Ramanna and Watts 2012; Roychowdhury and Watts 2007; Beaver and Ryan 2005). Specifically, if a firm's book value of assets is below its market value, the firm faces lower enforcement of the accounting regulation and thus weaker threats to recognize asset impairments. However, once the firm's book value of assets exceeds its market value of assets, accounting regulation encourages auditors to scrutinize whether the asset impairment loss should be recognized and determine the amount of asset impairments, which will be booked against income from continuing operations. Thus, a BTM equal to 1 is the cutoff point where firms face a significant increase in the likelihood of long-lived asset impairments.

We implement a nonparametric local polynomial regression kink design (RKD, hereafter) to identify the causal effects of the increased asset impairment threats on a firm's innovation activities. This estimation only uses observations near the cutoff point and compares the *slope* on the left of the cutoff point with that on the right, i.e., kink. Since the firm's market value of assets cannot be precisely manipulated, firms are randomly distributed in a narrow band surrounding the cutoff point (Card et al. 2015). Therefore, the RKD allows us to identify the causal effects of an endogenous regressor (threats to recognize the impairment losses) that is a function of an observable assignment variable (the BTM ratio) on the outcome variable (investment activities).

We first validate our identifying assumption that the BTM equal to 1 is the cut-off point with respect to the asset impairment threats. Consistent with prior research (e.g., Lawrence et al. 2013), we find that both the probability and the amount of asset impairments exhibit a significant kink (i.e., a sharp increase in the slope) across the cutoff point within the narrow band, supporting our identification strategy.[4] We also examine audit fees and find that they also show a significantly positive kink around the cut-off point, substantiating our argument that firms experience a significant increase in audit enforcement stemming from the increased asset impairment threats.

Next, we turn to our main prediction and examine whether firms that experience increased threats of asset impairments alter their internal innovation strategies. We specifically focus on research and development activities (R&D) because an increase in R&D is a clear indicator of undertaking turnaround attempts aiming at growth reconfiguration (Quinn 1986; Hambrick and Schecter 1983; Crever and Taylor 2000; Karim 2009). We examine the changes of R&D around the cutoff point and find that R&D expenditures show a significantly positive kink, indicating that

[4] The change in slope is interpreted as change in speed. For example, the increase of the slope at the cutoff, i.e., BTM equal to 1, represents the increase of the impairment speed for a unit change of the BTM ratio on the right of the cutoff compared with that on the left.

the sensitivity of R&D to the BTM ratio increases abruptly if the BTM ratio exceeds 1. The change in slope estimates across the cutoff point suggests that a one standard deviation increase in the BTM ratio leads to a 9.52% (= 0.1012 × 0.38 / 0.9198) increase in R&D.[5] We also find that capital expenditures show a significantly positive kink around the cutoff point, suggesting that firms also increase investments in tangible assets to complement the new investments in innovation (Lach and Schankerman1989; and Lach and Rob 1996).

Having documented the primary finding of our paper, we perform several cross-sectional tests to corroborate our argument. First, we expect that firms with greater access to external financing would have greater resources available to pursue organizational reconfiguration (Wan and Yiu 2009; Charkrabarti 2015). Consistent with our expectation, we find that firms with more external financing and assets exhibit a stronger kink effect in response to increased asset impairment threats. Second, organization theory suggests that older firms tend to have a higher degree of organization inertia and resistance to external governance (Hannan and Freeman 1984). Along this line, we find that younger firms are associated with a more significant kink effect when the threat of asset impairments increases. Third, we expect to find a stronger kink effect for firms with lower sales growth relative to that of the industry because the need to pursue growth reconfiguration would be stronger in such a case (Barker and Duhaime 1997). We again find consistent evidence.

Since the effectiveness of any regulation hinges on strong enforcement, we further expect that high-quality auditors would impose a greater threat of asset impairments when there is an indicator for the asset impairments, leading to more pronounced changes in R&D and capital investments. Following prior studies, we use Big 4 auditors, auditor industry expertise, and audit

[5] 0.1012 is the estimated kink of R&D. 0.38 is one standard deviation for the probability of impairments. 0.9198 is the estimated kink of the probability of impairments.

fees to proxy for audit quality (DeAngelo 1981; Frankel et al. 2002; Ferguson et al. 2003). Consistent with our prediction, we find that the kink effects on R&D and capital investment around the cutoff point are more pronounced when audit quality is higher. These findings strengthen our argument that the kink effects are driven by the enforcement of accounting regulation.

For further insights, we additionally examine whether the increased threats of asset impairments alter the external growth strategies (i.e., M&As). Firms can pursue growth either externally through M&As or internally by increasing R&D (Pitts 1977). Firms compare the cost of conducting R&D plus the cost of internal administration for internal developments with the sum of acquisition price and other transaction costs for market exchange (Williamson 1991, 2000). Increased threats of goodwill impairments indicate that the carrying value of the reporting unit, including goodwill, is higher than the recoverable amount. Moreover, it also increases the purchase price and transaction costs in a future M&A due to the adverse signaling effect on managerial abilities (e.g., Chen and Lin, 2018). Thus, we expect that the increase in asset impairment threats would increase the costs of engaging in M&A activities and other disciplinary forces, shifting the firm's growth strategies from external M&As to internal R&D. Consistent with our expectation, we find that M&A activities exhibit a significantly negative kink with respect to the BTM ratio. This finding provides additional insight as to how the accounting regulation of the asset impairments shapes the choice of the growth strategies of the firm.

To strengthen our inferences, we conduct several additional tests. First, we examine patenting activities in the future, which are the outcome of the increased R&D and thus an ex-post measure of innovation (Brown et al. 2009; He and Tian 2013; Tian and Wang 2014). We find that the number of patent filings in the future periods exhibits a significantly positive kink around the cutoff point. Furthermore, we find that the quality of the patenting activities in the future periods also increases as evidenced by a significantly positive kink of the average number of citations per patent around the cutoff point. These results bolster our inference and suggest that managers exert real efforts to improve the future growth of the firm when their current business models and existing assets turn out to be obsolete. Second, we examine the pre-SFAS 142 period and do not find a significant kink around the cutoff point for both R&D and M&A. This finding suggests that the effects of the increased asset impairment threats are indeed driven by accounting regulation of asset impairments. Third, we find that our estimation results are robust to alternative bandwidths and RKD specifications with high-order polynomials.

Our paper contributes to the literature in the following four ways. First, our paper extends the growing literature on the real effects of accounting reports. The extant studies extensively focus on whether the attributes of financial reports, such as accruals quality, affect corporate investment decisions (Biddle et al. 2009; Shroff 2017; Christensen et al. 2017, Zhong 2018). For example, Shroff et al. (2016) document that obtaining a financial statement audit reduces financing frictions, increasing corporate investments. Shroff (2017) documents that general U.S. GAAP changes have implications in corporate investments. Biddle et al. (2009) find that accounting transparency is associated with higher capital investment efficiency. We focus on specific accounting rules on asset impairments that are most relevant to corporate investment activities and establish a causal effect of asset impairment threats on firm innovation, which is the primary driver of long-term economic growth (Krugman 1979; Porter 1992; Aghion et al. 2013; Denning 2015; Laux and Stocken 2018).

Second, our paper contributes to the accounting literature on asset impairments. The vast majority of prior studies focus on managerial manipulation and generally conclude that managers use discretion regarding asset impairments to report opportunistically in response to the increased threats of asset impairments (e.g., Francis et al. 1996; Riedl 2004; Beatty and Weber 2006; Hayn and Hughes 2006; Ramanna 2008; Ramanna and Watts 2012; Li and Sloan 2017). Even though managerial opportunism is an important aspect, financial reporting has other positive economic roles (Ball 2008).[6] Our paper provides new insights as to how the asset impairment accounting changes managerial investment behavior to add value to the firm.

Third, our paper highlights the role of accounting regulation as a corporate governance mechanism that enhances firm innovation. Prior literature primarily examines internal governance mechanisms such as concentrated vs. dispersed ownership structure, institutional investors' holdings, debt vs. equity financing, and external institutions such as anti-takeover provisions and enforcement level of regulation.[7] Our paper extends this line of research and examines the role of accounting regulation and its enforcement in promoting firm innovation (e.g., Chang et al. 2015; Zhong 2018). Theoretically, Laux and Stocken (2018) suggest that accounting standards for financial reporting can act as an accelerator for innovation. We provide a timely empirical confirmation that accounting regulation of long-lived asset impairments can help organizations correct resource misallocation and prompt innovations.

Fourth, since our identification relies on firms lying in a narrow band surrounding the cutoff point where the BTM ratio equals 1, sample firms in our paper can be regarded as distressed firms. The conventional wisdom is that distress inhibits M&A or R&D activities since investments made by distressed firms are more vulnerable to the risk-shifting problem (Jensen and Meckling

[6] Ball (2008) states that "I am continually dismayed by the number of accounting professors and students who appear to believe financial reporting practice arises merely from some combination of (1) FASB standards and (2) managers cheating. […] The belief that earnings management is pervasive has become so entrenched in the literature that the mere existence of accruals has become a popular indicator of poor financial reporting quality."

[7] These mechanisms include firm specific institutions such as concentrated ownership (e.g., Hill and Snell 1988; Holmstrom 1989; Francis and Smith 1995; Lacetera 2001; Miozzo and Dewick 2002) and institutional investor monitoring (e.g., Aghion et al. 2013), and macro-institutions such as anti-takeover laws (e.g., Shleifer and Summers 1988; Stein 1988; Lazonick 2007; Atanassov 2013; Sapra et al. 2014).

1976). The debt overhang problem also discourages distressed firms from engaging in new investments (Myers 1977). However, a surprising fact is that distressed firms engage in substantial R&D and M&A activities, which are comparable to that of healthy firms.[8] The empirical data appears to suggest that a search for new growth engines by distressed firms is a type of "turnaround" strategy (e.g., Iyer and Miller 2008; Pearce II and Robbins 1993; Trahms, Ndofor, and Sirmon 2013). However, questions about whether distressed firms' investments are on average driven by agency problems, or whether distressed firms are actively seeking value-increasing growth engines, are unexplored by the finance and accounting literature. Our findings suggest that an increase in R&D by distressed firms due to the enforcement of accounting regulation generates more and higher quality patents, indirectly implying that distressed firms actively search for new value-increasing growth engines. Our results on the substitution between R&D and M&A resulting from the enforcement of accounting regulation of asset impairments also shed light on the discussion about organic or acquisitive growth strategies (Pitts 1977; Williamson 1991, 2000).

2. Regulatory settings and identification strategy

2.1. Why do we exploit the asset impairment setting?

Our primary research question is to examine whether asset impairment threats imposed by accounting regulation affect a firm's innovation and growth activities. In doing so, we exploit U.S. GAAP that regulates long-lived asset impairments, i.e., SFAS 142 and SFAS 144, which we describe in detail in the next section. SFAS 142 and SFAS 144 are the accounting regulations that

[8] During 2010 to 2014, over 28% of the acquisitions made by U.S. public firms came from distressed firms, although their market value only accounts for less than 18% of the aggregated market capitalization of all listed firms (Zhang 2016). Based on our data, the R&D made by firms lying within a narrow band surrounding a cutoff point (i.e., BTM $\in [0.823, 1.177]$) accounts for 21% of the total R&D made by all listed firms, and their total market capitalization accounts for 28% of the total market capitalization of all listed firms.

require periodic evaluation of past investments, and thereby, they have direct implications for a firm's subsequent investment and growth strategies. Specifically, SFAS 142 and 144 provide detailed guidelines on when and how much to adjust balances of previous investments if those past investments are not expected to generate returns sufficient to recover the investment costs. Therefore, this periodic assessment of the past investments facilitates the organization's learning process and thereby allows managers, corporate boards, and other stakeholders of the firm to update their beliefs regarding the firm's growth strategies. (Cyert and March 1963; Levinthal and March 1981).

Prior studies show that the realized impairment losses recognized in the financial statements give rise to significant adverse impacts on firm operations and reputation. Li et al. (2011) document negative abnormal returns around three-day windows of the impairment announcement date, and the negative abnormal returns are positively associated with the amount of impairment loss recognition. Ghosh et al. (2019) find that goodwill impairment is associated with the increased likelihood of CEO turnover. The asset write-offs are directly connected to covenants in debt contracts (Beatty and Weber 2006; Frankel et al. 2008) and executives' compensation payments (Beatty and Weber 2006; Edmans et al. 2016). Therefore, expecting these negative economic consequences, managers and corporate boards would have strong incentives to change their investment strategies in response to the periodic assessment of the past investments required by accounting regulation.

2.2. Long-lived asset impairment tests

SFAS 142 and SFAS 144 deal with the accounting issues of long-lived asset impairments. First, SFAS 142 provides detailed guidelines concerning the recognition of goodwill impairments. The goodwill impairment test is performed at least annually at the reporting unit level. For a given reporting unit, the test is a two-step procedure. The first step identifies a potential impairment by comparing the fair value of a reporting unit with its carrying amount including goodwill. If the fair value exceeds the carrying amount, the goodwill of the reporting unit is considered not impaired, and the second step of the impairment test is unnecessary. If the carrying amount exceeds the fair value, the second step measures the amount of goodwill impairment loss as the difference between the carrying amount of goodwill and the fair value of goodwill (SFAS 142 Paragraph 19 & 20, 2001).

SFAS 144 regulates the impairment of assets to be held and used. If an entity experiences events or changes in circumstances that indicate a change in the carrying amount of an asset that the entity expects to hold, the entity shall estimate the future cash flows expected to result from the use of the asset. If the sum of the expected future cash flows is less than the carrying amount of the asset, the entity recognizes an impairment loss as the amount by which the carrying amount of the asset exceeds the fair value of the asset (SFAS 121 Paragraph 5, 6, &7, 1995).[9]

The concept that impairment loss recognition of long-lived assets changes around a BTM ratio equal to 1 is addressed in prior studies. Lawrence et al. (2013) summarize the conceptual relation between asset write-downs and the BTM ratio.[10] They describe the relationship as a piecewise linear relation: flat line (slope equal to 0) in the regional BTM ratio less than 1 and linear line (slope equal to 1) in the regional BTM ratio greater than 1. Ramanna and Watts (2012) use a sample of firms whose BTM ratios are greater than 1 to examine the managers' motivations for goodwill impairment decisions. Prior studies use the BTM ratios as control variables in their regression models when the research question examines goodwill impairment loss recognition or

[9] SFAS 144 retains the requirements of SFAS 121 to recognize an impairment loss for long-lived assets to be held and used.
[10] See Figure 1 in Lawrence et al. (2013).

long-lived asset impairment loss recognition as a setting to test research questions (Beatty and Weber 2006; Frankel et al. 2008; Roychowdhury and Martin 2013; Sun 2015).

2.3. Regression kink design

The idea of the nonparametric local polynomial regression kink design (RKD) is to study the effects of the treatment using only observations in a neighborhood of the cutoff point small enough to control for unobserved confounders and to exploit the slope coefficient changes within these neighborhoods. RKD estimation allows researchers to overcome endogeneity issues in the OLS framework when the instrumental variable is hard to find. In various institutional settings, a key policy variable is set by a deterministic formula that depends on an endogenous assignment variable. When the policy function is *continuous* but kinked at a known threshold, RKD provides a potential way to overcome endogeneity issues and make a causal inference (Card et al. 2015).[11] Nonparametric local polynomial RKD estimation only uses observations near the cutoff point and compares the kink in the left of the cutoff point to the kink in the right of the cutoff point. Specifically, by restricting the estimation region very locally, the RKD allows for identification of the impact of an endogenous regressor (i.e., goodwill/long-lived asset impairment loss in our setting) that is a function of an observable assignment variable (i.e., BTM ratio). Also, we can estimate the data-driven optimal bandwidth that will minimize mean squared error for each outcome variable with different polynomial orders of the estimation model.[12]

[11] Card et al. (2015) establish conditions for RKD to identify a "treatment-on-the-treated" parameter. The key identifying assumptions are: (1) conditional on the unobservable determinants of the outcome variable, (2) the density of the assignment variable is smooth (i.e., continuously differentiable) at the kink in the policy rule, and (3) the treatment assignment rule is continuous at the kink point.

[12] The optimal bandwidth enables us to overcome the issues in the ad hoc definition of bandwidth that prior research typically employs. Also, the nonparametric local polynomial RKD design has another advantage over OLS estimation. Under the OLS framework, the variable of interest and correlated omitted variables (both those included and those omitted) are assumed as linear, and the omitted variables are additively separable from the variable of interest, which facilitates research design. However, there is no such evidence that managers choose a particular decision while all other decisions are fixed or held consistent. Therefore, it is likely that the linearity assumptions may not be justified.

Due to the above advantages of RKD, our identification strategy uses the kink in the impairment loss function around the BTM ratio equal to 1. Following Card et al. (2015), we interpret the kink as the exogenous variation of firms' exposures to goodwill and long-lived impairment loss recognition. Then, we estimate the kink in a firm's R&D activities around a BTM ratio equal to 1 to examine how the increased exposure to impairment loss recognition changes firm innovation and investment strategies of the firm.

3. Data

We use the Compustat database to obtain annual accounting data. We require the sample period to be from 2004 to 2017.[13] We require non-missing observations of total assets, the book value of equity, the number of shares outstanding, and share price.[14] Then, for each test, we require a non-missing value of corresponding outcome variables. For the tests using patent filing and the citation ratio, we use patent data used in Kogan et al. (2017). Because patent data is only provided until the year 2009, and we examine patents in period *t+1*, we examine patent filing and the citation ratio from 2004 to 2008. For merger and acquisition data, we use acquisition data from SDC. The sample period for acquisition data is from 2004 to 2015.

4. Empirical results

Fields et al. (2001) and Dechow et al. (2010) note that the linear independence assumption might be invalid in accounting decision-making.

[13] Both SFAS 142 and SFAS 144 were revised in 2001. There were no updates on regulation related to long-lived asset impairment, but substantial revision for goodwill impairment occurred in 2001. For fiscal year 2002, which is the first year after the new rule, if the change in the regulation leads them to write down assets, U.S. GAAP allow firms to write down their assets in fiscal year 2002 and record impairment losses below income from continuing operations. If firms do not decide to write down assets in 2002, firms are required to record impairment losses above income from continuing operations in the future when they are writing down assets (Beatty and Weber 2006). Because firms may have different incentives in impairment loss recognition decisions in 2002 relative to other years, we include only observations from 2004 to 2017.

[14] We largely follow Lawrence et al. (2013) for data restrictions that are relevant for our setting.

4.1. The kink effect in goodwill/long-lived asset impairment loss recognition

4.1.1. Smooth density testing

A key identifying assumption for valid inference in the RKD is that the density of the assignment variable is smooth at the threshold. Intuitively, this assumption implies that the BTM ratio cannot be precisely manipulated. If managers are able to manipulate the BTM ratio, then we should observe discontinuity in density at the cutoff point (e.g., Burgshtaler and Dichev, 1998), and thereby the BTM ratio to the right and the BTM ratio to the left are no longer comparable. In addition, our identification strategy also relies on the assumption that the determinants of impairment of firms in our sample evolve smoothly with respect to changes in the BTM ratio around the cutoff point where the BTM ratio equals 1.

Figure 1 shows the distribution of the BTM ratio using 0.01 for the bin size. The distribution does not show discontinuity at a cutoff point where the BTM ratio equals 1, suggesting that precise manipulation does not exist for samples surrounding the cutoff point. We further examine this more formally by estimating the density of the BTM ratio near the cutoff point and test whether the density is discontinuous in Table 1. We test discontinuity in density at the cutoff point (i.e., manipulation testing) using a local polynomial density estimator. The results show that the smooth density hypothesis is not rejected.[15] In untabulated tests, we also find that key determinants of impairment evolve smoothly with respect to the BTM ratio around the cutoff point, which helps justify our identifying assumptions.

4.1.2. Kink estimation: Goodwill/long-lived asset impairment loss

In this section, we estimate the kink effects for goodwill/long-lived asset impairment losses and examine whether the probability and the recognized amount of impairment losses are

[15] The null hypothesis is that the densities of the left and the right of the cutoff are equal.

significantly different on the left- and right-hand sides of the BTM ratio equal to 1. Although impairment rules are set by SFAS 142 and 144, there is often some slippage between the theoretical value of impairment losses to be recorded by the stated rule and the realized value in the data in practice. Among many possible reasons for such disparity, one reason is due to the measurement errors that are omitted in the relation between impairment loss recognition and the BTM ratio at the firm level. That is, there are at least two potentially unobserved factors: 1) reporting unit and 2) calculation of the market value of underlying assets by managers.

We first examine the kink effects of goodwill and long-lived asset impairment losses. Table 3 Panel A examines the kink effects of the probability of impairment loss recognition. The dependent variable is an indicator variable equal to 1 when the firm writes off goodwill or long-lived assets in period *t*. Column 1 estimates the kink effects using a local linear model.

Following Calonico et al. (2014) and Calonico et al. (2016), we employ local linear estimation-based optimal bandwidths. Using the observations within the optimal narrow window around the cutoff point (the optimal bandwidth is 0.093 on each side), we show a significant and positive kink.[16] The coefficient suggests that the difference between the slope on the right-hand side of the cutoff point and that on the left-hand side of the cutoff point is 0.093. This also means that the sensitivity of the probability of impairment loss recognition increases by 0.618 (= 1.435 × 0.431) for a one standard deviation increase of the BTM ratio when the BTM ratio exceeds 1, suggesting an increase in the enforcement of accounting rules on impairments

One concern about local linear estimation is that the relationship between impairment recognition and the BTM ratio may not be linear when samples are restricted to those lying within a narrow bandwidth. In Column 2, we employ a local quadratic model to address this empirical

[16] Please see Appendix B for details on the optimal bandwidth estimation.

issue. Using the observations within the optimal bandwidth, we consistently show a positive and significant kink even if we account for potential nonlinearity in the relationship between impairment recognition and the BTM ratio. The magnitude of the coefficient suggests that the difference between the slope on the right-hand side of the cutoff point and that on the left-hand side of the cutoff point is 1.98, which is qualitatively similar to that based on local linear estimation.

In Panel B, instead of examining the probability of goodwill or long-lived asset impairment loss, we use the amount of impairment loss as a dependent variable. The results are consistent with those in Panel A. Using the observations within the optimal bandwidth (i.e., the bandwidth is 0.115 on each side), we show a positive and significant kink. The magnitude suggests that the sensitivity of the amount of impairment loss recognition increases by 0.165 （=0.383×0.431） for a one standard deviation increase of the BTM ratio when the BTM ratio exceeds 1.

Figure 2 provides a graphical illustration of the estimation results in Table 3. Panel A plots the kink effects for the probability of impairment loss recognition. The Y-axis is the indicator of impairment loss recognition in period *t*, and the X-axis is the BTM ratio at the end of period *t*. A.1. (A.2.) is the graphical evidence of the kink effects using a local linear (quadratic) model. For A.1., the small dots in the figure are the average of the indicator variable in the non-overlapping window of the BTM ratio. We only display the plots using the data within the optimal bandwidth that is estimated in Table 3 Panel A. The solid line represents the slope using either a linear model (polynomial order of 1) or a quadratic model (polynomial order of 2). Similarly, Panel B plots the kink effects using the amount of impairment loss in period *t* against the BTM ratio at the end of period *t*. Overall, the graphical representation supports the statistical tests that show a significant kink in recognition of goodwill impairment loss and long-lived asset impairment loss at a BTM equal to 1. Combined with the results reported in Table 3, we conclude that firms are exposed to a significantly increased threat to recognize asset write-offs if the BTM ratio exceeds 1.

4.2. The kink effect on corporate innovation

In the previous section, we document a kink effect on asset impairment loss, suggesting an increase in threats for firms to recognize asset impairments per unit increase in the BTM ratio once their BTM ratios exceed 1. In this section, we examine to what extent such an increase in the threat would affect firms' investment decisions in the form of R&D and capital expenditures. Specifically, we examine whether R&D expenditures and capital expenditures exhibit positive slope changes when the BTM ratio exceeds 1.

Table 4 Panel A examines the kink effects of R&D in period *t+1* as a proxy for inputs of firm innovation. Column 1 estimates the kink effects for R&D using a full sample analysis. Using samples lying within the optimal bandwidth (i.e., 0.250 on each side), we find a positive and significant kink when the BTM ratios evolve around the cutoff point. The coefficient suggests that the difference between the slope on the right of the cutoff point and on the left of the cutoff point is 0.201. We employ the following equation to estimate the economic link between impairment threat and firm innovation activities:

$$\Delta Innovation\ Activitie_{s,\, t+1} = \Delta\beta_1 / \Delta\beta_s$$

where $\Delta Innovation\ Activitie_{s,\, t+1}$ is the change in innovation activity measure *s*; $\Delta\beta_1$ is the change in the impairment threat elasticity of the BTM ratio due to exceeding the cutoff point (i.e., change in slope, $\Delta\beta_1$ in Table 3), and $\Delta\beta_s$ is the change in the innovation activity *s* elasticity of the BTM ratio due to exceeding the cutoff point($\Delta\beta_s$).[17] Therefore, together with the estimation in Table 3, we find that a one standard deviation increase in the likelihood of recognizing impairment losses

[17] Please refer to appendix B for more details.

would lead to a 0.0535 (= 0.382 × 0.201 / 1.435) increase in R&D expenses, which is economically significant.

Prior studies show that investments in tangible assets intangible complement intangible investments (Lach and Schankerman 1989; Lach and Rob 1996; Chiao 2001). Therefore, when firms increase their investments in intangible assets, we may also expect to observe an increase in investments in tangible assets. To test this conjecture, we examine whether the sensitivity of capital investments to the BTM ratio also exhibits a kink around the cutoff point in Panel B. Using samples lying within the optimal bandwidth (i.e., 0.084 on each side), we find that the sensitivity of capital investment to the BTM ratio also exhibits a positive and significant kink when the BTM ratio exceeds 1.

4.3. Cross-sectional analyses

4.3.1. Firm heterogeneities

Firm heterogeneities would impose incremental effects on how they respond to an updated belief about past actions. Studies on organization theory suggest that the level of firm resources affects a declining firm's capacity to implement strategic change (Hedberg et al. 1976; Starbuck et al. 1978). For example, having access to external financing can provide a firm with more options for strategic change (e.g., Grinyer et al. 1988). In addition, large firms are endowed with more resources and have a superior market position to overcome entry barriers and implement strategic change (Porter, 1980) Therefore, we conjecture firms with more new external financing and larger firms are associated with a greater kink effect on R&D and capital investments when the threat of impairment recognition increases.

In Panel A of Table 5, we separate the sample into two sub-samples based on the median level of new external financing in period *t* and then run our main estimation using each sub-sample, respectively. Consistent with our prediction, firms with greater access to external financing exhibit a more pronounced kink effect on R&D and capital investments when the threat of impairment recognition increases ($R\&D_{t+1}$: 0.330 vs. 0.125; $CAPX_{t+1}$: 0.933 vs. 0.790). For example, the kink effect on R&D investment is approximately 2.6 times larger for firms with greater access to external financing compared to that of firms with less access to external financing. Similarly, we separate the full sample into two sub-samples based on firm size at the beginning of period *t* and then re-estimate our main specification. The results in Panel B show that larger firms are associated with a greater kink effect on R&D and capital investments when the threat of impairment recognition increases ($R\&D_{t+1}$: 0.139 vs. 0.078; $CAPX_{t+1}$: 1.180 vs. 0.380). As for economic magnitude, the kink effect on R&D investment is approximately 1.7 times larger for larger firms compared to that of smaller firms.

We further conjecture that younger firms are associated with a greater kink effect due to the following results. First, younger firms rely more on a trial-and-error learning process when changing growth strategies due to a lack of experience. Second, younger firms are associated with a lower degree of organization inertia and a lower degree of resistant to external governance (Hannan and Freeman, 1984). In Panel C of Table 5, we separate the sample into two sub-samples based on the median level of firm age in period *t* and then run our main estimation using each sub-sample. Consistent with our prediction, younger firms exhibit a more pronounced kink effect on R&D and capital investments when the threat of impairment recognition increases ($R\&D_{t+1}$: 0.377 vs. 0.035; $CAPX_{t+1}$: 0.893 vs. 0.651). Third, firms with different access to growth opportunities would respond differently when the threat of asset impairments increases. More specifically, if a firm's main industry is growing concurrent with the firm's decline, then the need to pursue growth, reconfiguration would be stronger (Barker and Duhaime, 1997). To test this conjecture, In Panel

D of Table 5, we separate the sample into two sub-samples based on the median level of the gap between industry growth and firm growth in period *t*, and then estimate the main specification using each sub-sample respectively. Consistent with our prediction, a larger gap between industry growth and firm growth would lead to a greater kink effect on R&D and capital investments when the threat of impairment recognition increases ($R\&D_{t+1}$: 0.407 vs. 0.097; $CAPX_{t+1}$: 0.878 vs. 0.872).

4.3.2. Auditor enforcement

The effectiveness of accounting rules largely relies on whether auditor monitoring and enforcement are strong. Prior studies show that large auditors have greater aggregate quasi-rents, which effectively serve as collaterals against compromises in the auditing process (DeAngelo 1981). Therefore, large auditors apply more stringent criteria when enforcing accounting rules. The deep pocket theory (Dye 1993) also suggests that the size of an auditor is positively associated with audit quality. Along this line, prior research finds that Big N auditors better prevent accounting manipulations (Becker et al. 1998; Teoh and Wong 1993). As such, we predict that firms audited by Big 4 auditors would face a greater threat of asset impairments when the BTM ratio exceeds 1, and therefore are more likely to implement growth reconfiguration.

To test this prediction, we first compare firms audited by Big N auditors to those audited by non-Big N auditors. The results are reported in Panel E of Table 5. Consistent with our expectation, we find that firms audited by Big 4 auditors exhibit a greater kink effect on R&D and capital investments ($R\&D_{t+1}$: 0.422 vs. 0.102; $CAPX_{t+1}$: 0.949 vs. 0.556). These findings reinforce our argument the changes in firms' investment policies are driven by the stringent enforcement of accounting rules on asset impairments.

In Panels F and G, we further separate the full sample into two sub-groups based on auditor industry expertise and audit fees, since these two variables are used as alternative proxies for auditing quality and therefore are positively related to the strength of audit enforcement (e.g., Frankel et al. 2002; Ferguson et al. 2003). We find consistent results that audit quality strengthens the association between our measure of the threat of asset impairments and the changes in R&D and capital investments ($R\&D_{t+1}$: 0.296 vs. 0.105; $CAPX_{t+1}$: 0.970 vs. 0.670 in Panel F, and $R\&D_{t+1}$: 0.264 vs. 0.133; $CAPX_{t+1}$: 1.055 vs. 0.685 in Panel G). In sum, our findings suggest that higher audit quality makes the asset impairment threats stronger, thereby leading to greater changes in R&D and capital investments.

4.4. Acquisitive growth vis-a-vis organic growth

Firms can pursue growth either externally through M&As or internally by increasing R&D (Pitts 1977). Firms will compare the cost of conducting R&D plus the cost of internal administration for internal development to the sum of the acquisition price and other transaction costs for market exchange (e.g., Williamson1991, 2000). An increased likelihood of goodwill impairment recognition indicates that the acquisition price and other transaction costs for market exchange are higher than the previously expected level. It also increases the purchase price and transaction costs in future M&As due to the adverse signaling effect on managerial abilities. We note that due to agency problems, managers opt to over-invest in M&As compared to internal R&D (Jensen 1986 and 1988; Holmstrom 1989; Agrawal, Jaffe and Mandelker 1992; Loughran and Vijh 1997; Holmstrom and Roberts 1998; Harford 1999; Harford and Li 2007).[18] To the extent that the enforcement of impairment accounting facilitates the trial-and-error learning process, we should expect a decrease in M&A activities when the threat of recognizing asset impairment

[18] There are some reasons driving managers to prefer M&As over R&D. For example, Harford and Li (2007) directly show that executive pay increases more than 200% immediately after engaging in M&As. However, shareholders may not compensate managers for their investments in R&D but could impose penalties on managers for failures in innovative projects due to the information asymmetry (Holmstrom 1989).

increases.[19] Therefore, we predict that, when the BTM ratio exceeds 1, the increased marginal costs of engaging in M&A activities due to the increased threats of asset impairments will discourage managers from conducting further M&A activities, and will encourage managers to invest more in internal R&D. That is, there could be a resource re-allocation from external M&A activities to internal R&D activities when the threats of asset impairments increase.

Table 6 Panel A reports our estimation using samples lying within the optimal bandwidth (i.e., 0.269 on each side). Consistent with our prediction, we find a negative and significant kink in M&A activities when firms' BTM ratios exceed 1. The coefficient suggests that the difference between the slope on the right-hand side of the cutoff point and that on the left-hand side of the cutoff point is -0.081. The magnitude of the coefficient suggests that the sensitivity of engaging in M&As to the BTM ratio decreases by 3.491% (= 0.081 × 0.431) for a one standard deviation increase in the BTM ratio. Together with the estimation in Table 3, we find that a one standard deviation increase in the likelihood of recognizing impairment losses would lead to a 2.156% (= 0.382 × 0.081 / 1.435) decrease in M&A likelihood, which is economically significant. In Panel B, we restrict our sample to those with goodwill (i.e., having M&A transactions in the past). We find a stronger kink effect for samples with goodwill.

Overall, we find that an increase in the threat of impairment recognition increases the investments in R&D but decreases the investments in M&As, suggesting a shift in firms' growth strategies from acquisitive growth to organic growth when the enforcement of accounting rules increases. Our findings support a corporate governance role of accounting rules.

4.5. Outcomes of internal innovation activities: Patent filings and citations

[19] Most of the impairment losses are due to the over-valuation problem in the prior M&A activities. An increase in the threat of recognizing impairment losses would put a red flag on investments in M&As, resulting in closer scrutiny from shareholders/boards on future M&A activities.

In this section, we examine the long-run effect of the increase in R&D activities due to the increased threat of impairment recognition. In particular, we examine the kink effect on patent filling activities and patent quality proxied by per patent citations when firms' BTM ratios exceed 1. Arguably, if an increase in R&D activities due to the increased threat of impairment recognition reflects a correction mechanism that encourages managers to focus more on the value-increasing innovative projects, one should expect an increase in patent activities and patent quality in the long run.

Table 7 examines the kink effects on yearly patent filing activities from period *t+1* to period *t+3* using samples lying within the optimal bandwidth (i.e., 0.402 on each side). Consistent with our prediction, we find a positive and significant kink effect on patent activities during period *t*+1 to period *t*+3 when firms' BTM ratios exceed 1. The difference between the slope on the right-hand side of the cutoff point and that on the left-hand side of the cutoff point is 0.600. Together with the estimation in Table 3, we find that a one standard deviation increase in the likelihood of recognizing impairment losses would lead to a 0.160 (= 0.382 × 0.600 / 1.435) increase in long-run patent filing activities. Given that the mean value of patent filing is 2.85, the estimated treatment effect can be translated into a 5.604% increase in patenting activities, which is economically significant.

Using samples lying within the optimal bandwidth (i.e., 0.365 on each side), we further examine the kink effect on patent quality proxied by the yearly per patent citations from period *t*+1 to period *t*+3. Consistent with this prediction, we find a positive and significant kink effect on per patent citations from period *t*+1 to period *t*+3 when firms' BTM ratios exceed 1 (shown in Table 8). The difference between the slope on the right-hand side of the cutoff point and that on the left-hand side of the cutoff point is 0.235. Together with the estimation in Table 3, we find that a one standard deviation increase in the likelihood of recognizing impairment losses would lead to a 0.063 (= 0.382 × 0.235 / 1.435) increase in the patent citation. Given that the mean value of average patent citation is 0.636, the estimated treatment effect can be translated into a 9.906% increase in patent quality.

Collectively, the statistical tests in this section show that firms that experience an increased threat of impairment recognition enhance their internal innovation activities, resulting in an increase in patent filing activities and an improvement in patent quality in the long run.

4.6. Robustness tests

4.6.1. Innovation kink effects in the pre-SFAS 142 period

In our main analysis, we use a two-step analysis of SFAS 142, i.e., U.S. GAAP on goodwill impairment loss. This analysis, which generates the increased threat on impairment recognition around the BTM of assets ratio equal to 1 and allows us to apply RK design, should not give the same result in the pre-SFAS 142 period. More specifically, SFAS 142 is implemented for fiscal years beginning after December 15, 2001. Because goodwill was recognized as an asset and amortized over no longer than 40 years before the adoption of this standard, we should fail to observe any significant kink effect on investment policies when the BTM ratio exceeds 1 when the sample period is before 2001. Therefore, using the sample period before the passage of SFAS 142 to conduct a falsification test can help strengthen the argument on the validity of our identification strategy.

Table 9 presents the results of kink effects on R&D expenses and M&A activities in pre-SFAS 142 periods. We find that R&D expenses and M&A activities exhibit a statistically insignificant kink effect, which is sharply different from that during the post-SFAS period.

4.6.2. Ad hoc bandwidths and alternative cutoffs

In our main tests, we follow Calonico et al. (2014) and Calonico et al. (2016) to employ an optimal bandwidth estimation. In this section, we test how the empirical results of kink effects vary as we change the bandwidth. To this end, we use a polynomial order of 1 and change the bandwidths from 0.07 to 0.25 for both the left and right sides of the cutoff point. Using different bandwidths, we come up with slightly different estimations (shown in Panel A of Table 10). However, these estimations consistently show that the sensitivity of corporate R&D to BTM ratios exhibits a positive kink when the BTM ratios exceed 1. That means, our findings are robust to alternative definitions of bandwidth,

In Panel B, we examine how the kink effects change when we move away from the cutoff point; the BTM ratio equals 1. To make our estimations more comparable across different cutoff points, we restrict the bandwidth to 0.15 on both left and right of the cutoff point for simplicity. Then, we move the cutoff points from 0.6 to 1.4 and re-estimate the kink effects using different samples resulting from using different cutoff points. For example, if the cutoff point is set to be 0.6, we then compare the region where the BTM ratios lie within (0.6 ~ 0.75) and the region where the BTM ratios lie within (0.45 ~ 0.6) and estimate the change in sensitivity of dependent variables to BTM ratios. The results reported in Panel B of Table 9 suggest that the significant increase in the threat of impairment loss recognition occurs only when we set the cutoff point to be 1.

4.6.3. Alternative explanation: Disclosing previously hidden R&D

One alternative explanation for the increase in reported R&D expenses could be that firms are incentivized to disclose previously hidden R&D expenses. Koh and Reed (2015) show that firms may strategically hide their real R&D expenses due to proprietary costs. They termed these missing R&D firms with patent activity as “pseudo-blank R&D firms.” When firms are facing an increased threat of recognizing impairments, they could be incentivized to disclose the previously hidden R&D expenses, leading to a positive kink effect on the reported R&D expenses. From this perspective, the observed increase in R&D expenses may merely reflect changes in disclosure strategies of the firm rather than real investment behavior. To test this alternative explanation, we directly examine the effect of an increased threat of recognizing impairments on the likelihood of having pseudo-blank R&D. We find the opposite result: there is a positive and significant kink effect on pseudo-blank R&D. That means, instead of disclosing previously hidden R&D expenses, firms choose to hide more R&D expenses. This finding is consistent with our argument that managers are incentivized to engage in value-increasing investment projects.

4.6.4. Auditor monitoring and enforcement

Last, we examine whether there is a positive kink effect on auditor screening and monitoring when the BTM ratio of a firm exceeds 1. Note that the enforcement of accounting rules largely relies on auditor screening and monitoring. If the enforcement of impairment accounting increases (i.e., an increased threat of impairment recognition), one would expect a corresponding increase in auditor effort proxied by auditor fees. To test this conjecture, we examine the change in sensitivity of an audit fee to the BTM ratio using samples lying within a narrow bandwidth around the cutoff point. The estimated results are reported in Table 12. Consistent with our prediction, we find a positive and significant kink effect on audit fees when the BTM ratio of a firm exceeds 1. This finding reinforces our argument that the enforcement of accounting rules increases the threat of impairment recognition and, therefore, changes firm innovation policies.

5. Conclusion

In this paper, using nonparametric local polynomial regression kink design, we examine whether accounting regulation of asset impairment affects firms' innovation activities. In the context of SFAS 142 and 144, we exploit exogenous variation of the threat of impairment loss recognition around a cutoff point where the BTM ratio equals 1. Using regression kink design, we first show that the sensitivity of the probability of recognizing asset impairments to the BTM ratio, and of the amount of asset impairments to the BTM ratio, significantly increases when the BTM ratio exceeds 1. Then, we identify that the sensitivity of R&D and capital investments to the BTM ratio increases, and the sensitivity of the M&A likelihood to the BTM ratio decreases when the BTM ratio exceeds 1. These findings are likely to reflect firms' changes in firm growth policies. More specifically, when firms are exposed to an increased threat of impairment recognition, they are more likely to undertake turnaround attempts emphasizing growth reconfiguration. Cross-sectional analyses show that the kink effect on R&D and capital investment is more pronounced for firms with greater access to new financing, larger firms, younger firms, and declining firms in industries with concurrent high growth.

These cross-sectional results strengthen our argument that increased exposure to the threat of impairment recognition incentivizes managers to change growth strategies. Further analyses reveal that the increase in internal innovation activities translates into more patent activities and a higher patent quality in the long run. Overall, our findings suggest that the enforcement of accounting rules incentivizes managers to search for new growth engines, resulting in a positive effect on corporate innovations.

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Appendix A Variable Definitions

Variables	Descriptions
BTM_t	BTM_t is the book-to-market ratio at the end of period *t* and defined as the book value of total assets before asset impairments divided by the market value of assets at the end of period *t*. The market value of assets is measured as the market value of equity plus the book value of total liabilities.
Impairment Indicator$_t$	*Impairment Indicator*$_t$ is an indicator equal to 1 if the sum of goodwill impairments and the long-lived assets write-downs in period *t* is positive, 0 otherwise.
Impairments$_t$	*Impairments*$_t$ is the amount of asset impairments in period *t* and measured as the sum of the goodwill impairments and the long-lived asset write-downs, scaled by the market value of equity at the beginning of period *t*.
$R\&D_{t+1}$	$R\&D_{t+1}$ is the R&D expenditures of the firm in period *t+1*, scaled by the market value of equity at the end of period *t*.
$CAPX_{t+1}$	$CAPX_{t+1}$ is the capital expenditures of the firm in period *t+1*, scaled by the market value of equity at the end of period *t*.
$Patents_{t+1,t+3}$	$Patents_{t+1,t+3}$ is the natural log of1 plus the number of patents filed between period *t+1* and *t+3*.
$Citation_{t+1,t+3}$	$Citation_{t+1,t+3}$ is the average of per-year citations of patents filed between period *t+1* and period *t+3*.
$M\&A_{t+1}$	$M\&A_{t+1}$ is an indicator equal to1 if an M&A transaction occurs in period *t+1*, 0 otherwise.
Missing $R\&D_{t+1}$	*Missing* $R\&D_{t+1}$ is an indicator equal to1 if a firm's R&D is missing in Compustat in period *t+1* while the firm reports at least one patent filing during the past 10 years (Koh and Reeb 2015)
Audit Fees$_t$	*Audit Fees*$_t$ is the natural log of 1 plus audit fees in period *t*.
New External Financing$_t$	*New External Financing*$_t$ is the sum of net debts and net equity issued in period *t*, divided by the total assets at the beginning of period *t*.
Firm Size$_t$	*Firm Size*$_t$ is the total assets in period *t*.
Firm Age$_t$	*Firm Age*$_t$ is the firm age in period *t*.
Relative Sales Growth$_t$	*Relative Sales Growth*$_t$ is the sales growth of the firm between period *t-1* and period *t* relative to the industry median sales growth between period *t-1* and period *t*. Industry is defined using a four-digit SIC.

Big N Auditor$_t$	*Big N Auditor$_t$* is an indicator equal to 1 if the firm's auditor is one of 4 big audit firms, 0 otherwise.
Auditor Industry Expertise$_t$	*Auditor Industry Expertise$_t$* is measured as the total assets of the auditor's clients in a given industry divided by the total assets of all firms in the same industry. Industry is defined by a two-digit SIC. Auditor is defined at the audit office level.
ROA$_t$	*ROA$_t$* is the return on assets in period t, which is measured as a firm's pretax income before special items in period t divided by total assets at the beginning of period t.
Leverage$_t$	*Leverage$_t$* is the long-term debt in period t divided by the total assets at the end of period t.

Appendix B Estimation Model

We build on a non-parametric local polynomial identification framework documented by Calanico et al. (2014) and Card et al. (2015), which allows non-separability of the error term. Card et al. (2015) study a general single kink model,

$$Y = y(P, X, U)$$

where *Y* is an outcome, *P* is a policy-related variable of interest, *X* is another observed covariate (assignment variable), and *U* is a potentially multidimensional error term that enters the function *y* in a non-additive way. We assume that *P* = *p*(*X*). The outcome variable *Y* is an innovation- and investment-related variable. *P* is goodwill/long-lived asset impairment loss recognition. *X* is the BTM ratio.[20] The treatment effect estimated using Kink Design can be described as,

$$T_{rk} = \frac{\frac{dE[Y_{1i} - Y_{0i} | X_i = x]}{dx}}{\frac{dE[P | X_i = x]}{dx}} = \frac{\frac{dE[Y_{1i} | X_i = x]}{dx} - \frac{dE[Y_{0i} | X_i = x]}{dx}}{\frac{dE[P | X_i = x]}{dx}} \qquad (1)$$

where i stands for units, Y_{1i} is the outcome when i is in the treated group, Y_{0i} is the outcome when i is in control group, and x is the cutoff point. Under the small window of h left of x and the small window of h right of x, i.e., $[x - h < X_i < x, x < X_i < x + h]$, equation (1) can be re-written as the following:

$$T_{rk} = \lim_{h \to 0} \frac{\frac{dE[Y_{1i} | x < X_i < x + h]}{dx}}{\frac{dE[P | x < X_i < x + h]}{dx}} - \lim_{h \to 0} \frac{\frac{dE[Y_{0i} | x - h < X_i < x]}{dx}}{\frac{dE[P | x - h < X_i < x]}{dx}} \qquad (2)$$

[20] We apply a Sharp RKD approach throughout the main arguments. In supplemental analysis, we also estimate the model using a Fuzzy RKD approach as a robustness check.

where x will be 1 in our setting (BTM equal to 1 is the cutoff point). Using a local polynomial estimation approach, we recover T_{rk} by estimating $\hat{T}_{rk}$in the following way:

$$\hat{T}_{rk} = \frac{\hat{\beta}_1^+ - \hat{\beta}_1^-}{\hat{R}_1^+ - \hat{R}_1^-} \qquad (3)$$

where

$$\widehat{\beta_1} = \underset{\{\beta_1\}}{\operatorname{argmin}} \sum_{i=1}^{N} \left\{Y_i - \sum_{j=0}^{p} \beta_j (X_i - x)^j\right\}^2 K\left(\frac{X_i - x}{h}\right) \qquad (4)$$

$$\widehat{R_1} = \underset{\{R_1\}}{\operatorname{argmin}} \sum_{i=1}^{N} \left\{P_i - \sum_{j=0}^{p} R_j (X_i - x)^j\right\}^2 K\left(\frac{X_i - x}{h}\right) \qquad (5)$$

In this equation, *N* stands for the number of observations in the bandwidth *h*, *K* is the kernel function that defines the weight given to the observations in bandwidth *h*, and *p* is the polynomial order of underlying conditional mean function of outcome Y_i within the bandwidth. $\hat{\beta}_1^+$ is the estimated coefficient of first order derivative (i.e., slope) of the underlying functional form that minimizes estimation error (i.e., Y_i- $\hat{Y}_i$) using the observations in the right window of cutoff $x = 1$. $\hat{\beta}_1^-$ is estimated using the observations in the left window of cutoff $x = 1$. Therefore, $\hat{\beta}_1^+ - \hat{\beta}_1^-$ is the difference of a slope estimated from the right side of window BTM equal to 1 and a slope estimated from the left side of window BTM equal to 1 in the relation between outcome *Y* (e.g., R&D, capital expenditure) and the BTM ratio. $\hat{R}_1^+ - \hat{R}_1^-$ is the difference between a slope estimated from the right side of window BTM equal to 1 and a slope estimated from the left side of window BTM equal to 1 in the relation between policy variable *P* (i.e., impairment loss recognition) and the BTM ratio.

Following Card et al. (2015), we estimate a local linear model (p = 1) and a local quadratic model (p = 2). We use a triangular kernel function which denotes higher weights to the observations that are closer to the cutoff point.[21] For bandwidth choice h, we estimate MSE (mean squared error) optimal bandwidth following Calonico et al. (2014) and Calonico et al. (2016).

Defining bandwidth (h) is very important in estimating the precise treatment effect (Lee and Lemiux, 2010). All the bandwidth choices available in the literature are obtained by balancing squared-bias and variance of the RD estimator.[22]

Lee and Lemiux (2010) address practical issues in selecting bandwidth in terms of the trade-off between bias and precision of the estimated treatment effect.[23] On the one hand, in finite samples, the bandwidth has to be large enough to include enough observations to get a reasonable amount of precision in the estimation of predicted values of Y. Thus, using a larger bandwidth provides more precise estimates as more observations are available to estimate the underlying model. On the other hand, the increase in bandwidth comes at the cost of bias in the estimated treatment effect. In other words, when bandwidth is relatively large, the estimated kink effect will

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[21] The triangular kernel is $K(u/h) = (1 - |u|) \times 1_{|u|\leq 1}$ widely used in recent RD applications. The choice of kernel function turns out to be less important than the choice of bandwidth h (Kisin and Manela, 2015).

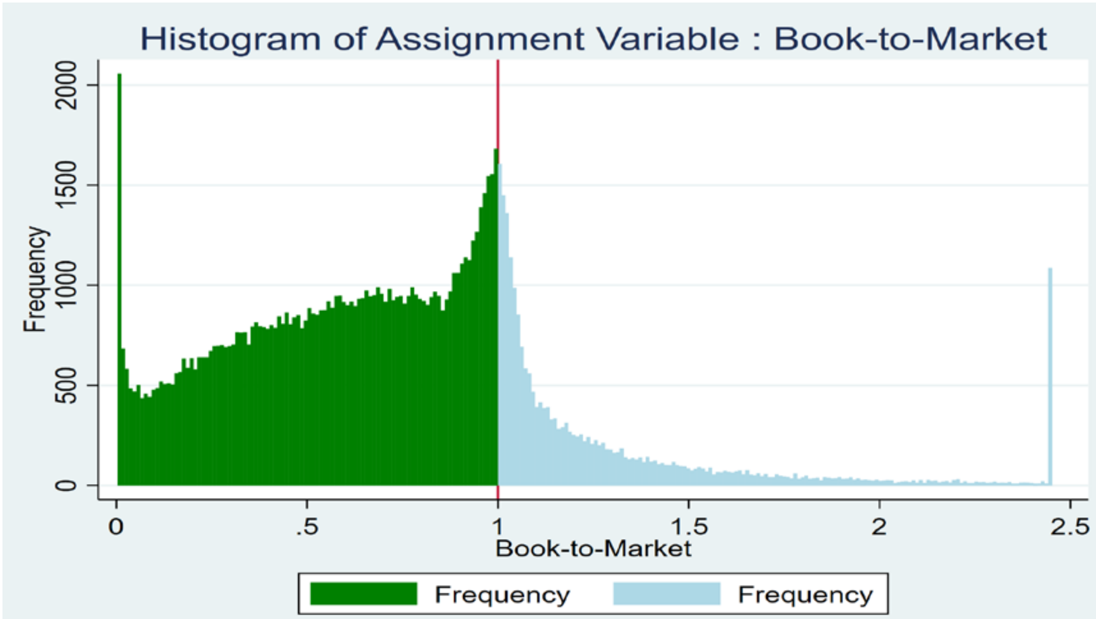
[22] The treatment effect estimator $\hat{T}(h)$ follows MSE (mean-squared error) expansion. Let $X_n = (X_1,\ X_2,\ \ldots.X_n)'$. $MSE\ (h_n) = E\left[\ \left\{\hat{T}(h_n)\ - T\right\}^2 |X_n\right] \approx h_n^{2(p+1)} {B_n}^2 + \frac{1}{nh_n} V_b$, with $B_n \rightarrow B$ and $V_n \rightarrow V$ where B and V represent, respectively, the asymptotic bias and the asymptotic variance of $\hat{T}\ (h_n)$. p is the polynomial order and n is the number of observations within bandwidth h. This treatment effect estimator will be consistent if $h_n \rightarrow 0$ and $nh_n \rightarrow \infty$. Moreover, the point estimator $\hat{T}\ (h_n)$ will be optimal in an asymptotic MSE sense if the bandwidth h_n is chosen so that $h_{mse,\,n} = \left[\frac{V/n}{2(1+p)B^2}\right]^{\frac{1}{3+2p}}$. The bandwidth in tables is calculated by this function (Calonico et al. 2016). The STATA code for estimation is *rdrobust*.

[23] As shown in footnote 22, bandwidth (h) enters into the function as a multiplication term with the bias term (B) while bandwidth (h) enters into the function as inverse-multiplication term with the variance term (V). Therefore, as optimal bandwidth increases, bias has more impact on determining MSE (mean-squared error) while as bandwidth decreases, variance has more impact on determining MSE. Therefore, the "relatively large" bandwidth will be optimal in a sense of minimizing MSE, but the estimated treatment effect using the "relatively large" bandwidth might be biased.

have less variability (higher precision), but the estimated kink effect might be different from the actual kink effect (i.e., biased estimation). In short, the bias and precision can be described as the following: the attempts to reduce the bias by shrinking the bandwidth will result in an extremely noisy estimation of the treatment effect, while the attempts to reduce the nosiness of estimation by increasing the bandwidth will result in biased estimation of the treatment effect. All bandwidths chosen to estimate kink effects in this paper are selected optimally to minimize the mean-squared error of estimated kink effect $\hat{T}_{rk}$ instead of being chosen ad hoc, which is the approach most prior studies in finance and accounting take.

In order to conservatively estimate kink effects, we estimate the kink effects using a triangular kernel function, which gives more weights on the observations that are closer to the cutoff points.

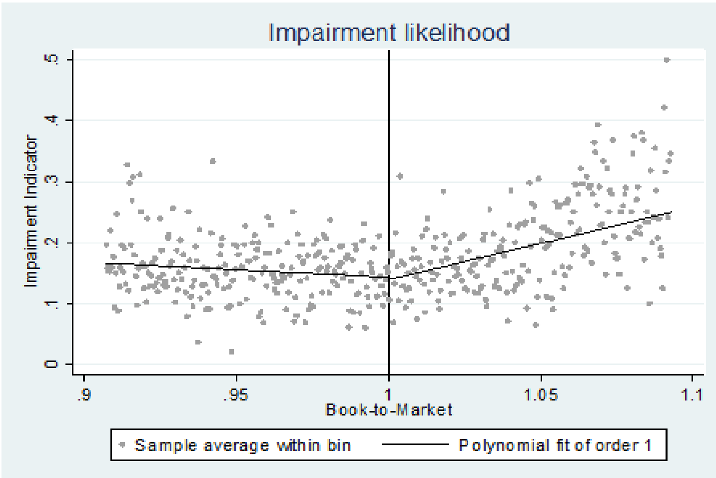
Figure 1 Histogram of assignment variable: Book-To-Market ratio (BTM)



This figure shows the density of the BTM ratio. Regression kink design can be invalid if individuals can *precisely* manipulate the assignment variable, i.e., the BTM ratio, (Lee and Lemieux 2010). We test graphically the smoothness of the distribution of the assignment variable (BTM_t) at the kink point, i.e., $BTM_t = 1$. Figure 1 is the graphical representation of the underlying distribution. The bin size of both left and right is 0.01.

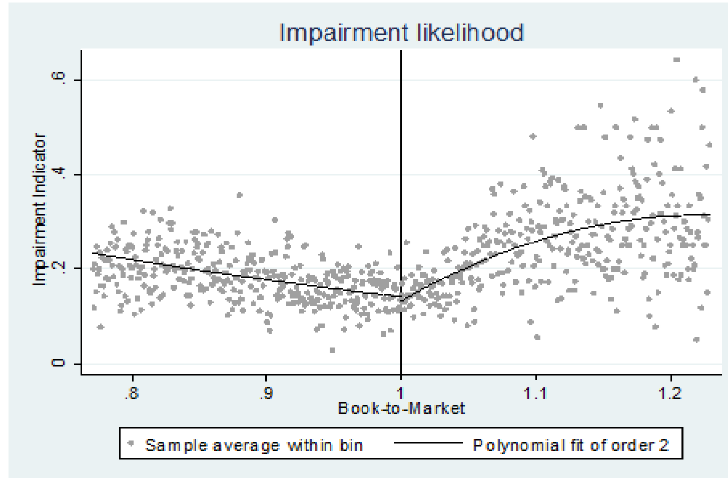
Figure 2 Asset impairments around BTM equal to 1

A.1.



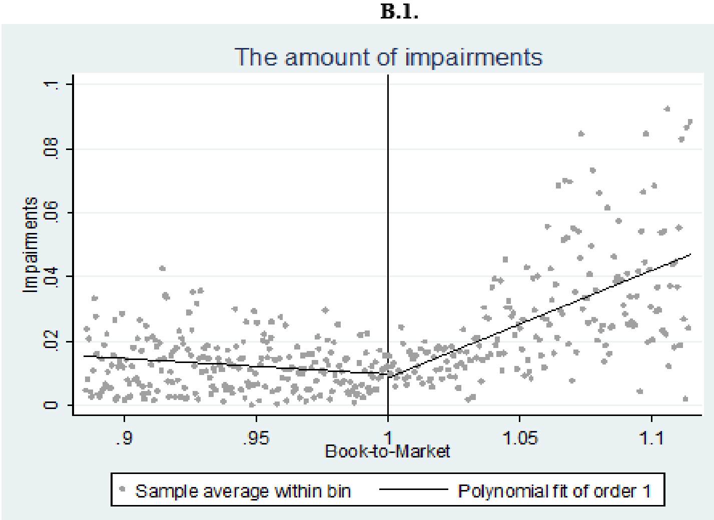
Bin size: Left (Right) of cut off 0.0005 (0.0005) / Bandwidth: Left (Right) 0.093 (0.093)

A.2.



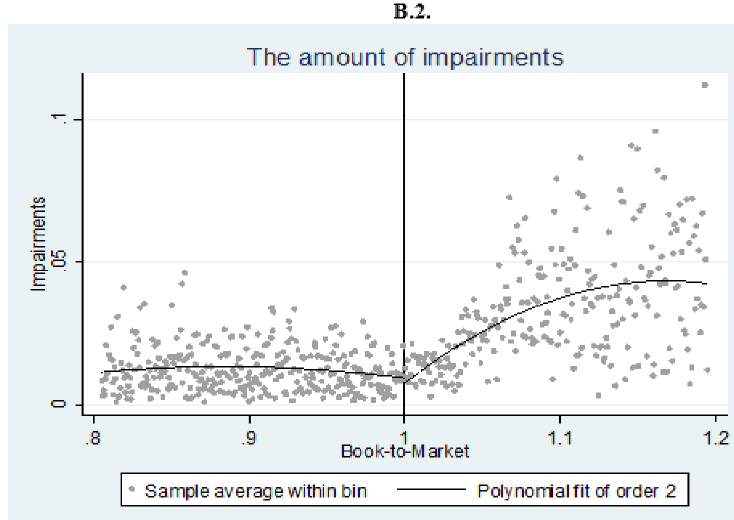
Bin size: Left (Right) of cut off 0.001 (0.001) / Bandwidth: Left (Right) 0.229 (0.229)

B.1.



Bin size: Left (Right) of cut off 0.0005 (0.0005) / Bandwidth: Left (Right) 0.115 (0.115)

B.2.

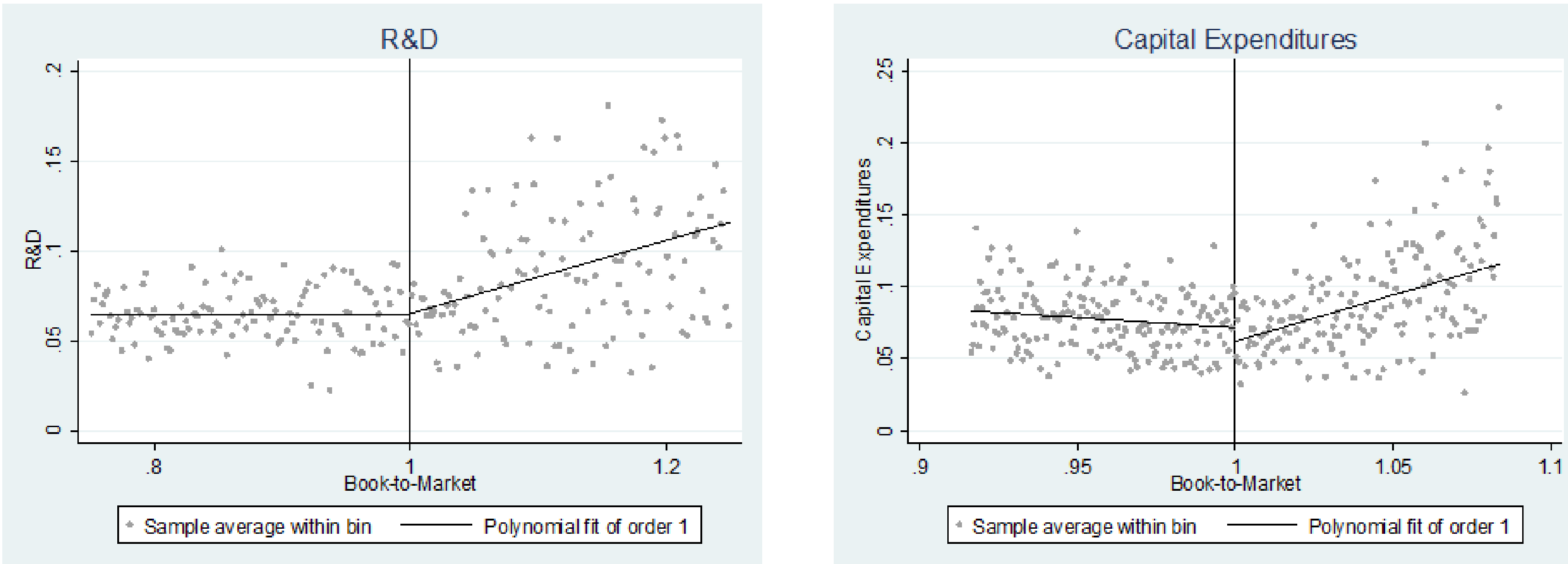


Bin size: Left (Right) of cut off 0.001 (0.001) / Bandwidth: Left (Right) 0.195 (0.195)

This figure illustrates the kink in asset impairments. In Figure A.1. and A.2., the Y-axis is the indicator of asset impairments in period *t* (*Impairment Indicator*$_t$), and the X-axis is the book-to-market ratio at the end of period *t* (*BTM*$_t$). In Figure B.1. and B.2., the Y-axis is the amount of asset impairments in period *t* (*Impairments*$_t$), and the X-axis is the book-to-market ratio at the end of period *t* (*BTM*$_t$). The plot is the average of the indicator of impairments (Figure A.1. and A.2.) or the amount of impairments (Figure B.1. and B.2.) within the small bin size. The lines display predicted values of the regression in the linear case, i.e., polynomial order = 1 (Figure A.1. and B.1), or in the quadratic case, i.e., polynomial order = 2 (Figure A.2. and B.2.). The lines are predicted only using the observations within the optimal bandwidth that are estimated in Table 3. The optimal bandwidth is calculated following Calonico et al. (2014) and Calonico et al. (2016).

Figure 3 R&D and capital expenditures around BTM equal to 1

A. **B.**



Bin size: Left (Right) of cut off 0.002 (0.002) / Bandwidth: Left (Right) 0.218 (0.218)

Bin size: Left (Right) of cut off 0.001 (0.001) / Bandwidth: Left (Right) 0.087 (0.087)

This figure illustrates the kink in R&D and capital expenditures in period *t+1*. Figure A. shows the kink effect of R&D in period *t+1*. Figure B. shows the kink effect of capital expenditures in period *t+1*. The plot is the average amount of R&D expenditures (left) and the average amount of capital expenditures (right) within the small bin size. The lines display predicted values of the regression in the linear case, i.e., polynomial order = 1. The lines are predicted only using the observations within the optimal bandwidth that are estimated in Table 4. The optimal bandwidth is calculated following Calonico et al. (2014) and Calonico et al. (2016).

Table 1 Continuous density tests

This table tests the discontinuity of density for assignment variable (BTM_t) at the cutoff point of the BTM ratio equal to 1 (i.e., manipulation tests using local polynomial density estimation). We test discontinuity using the linear model, i.e., polynomial order = 1, and the quadratic model, i.e., polynomial order = 2. The discontinuity of density is tested by estimating optimal bandwidth and using a triangular kernel function to provide more weights on the observations closer to the cutoff point. We follow Calonico et al. (2014) and Calonico et al. (2016) to perform a robustness test that accounts for potential large optimal bandwidth.

	Local Polynomial Order =1		Local Polynomial Order =2	
	Left of Cutoff point	Right of Cutoff point	Left of Cutoff point	Right of Cutoff point
Eff. Number of Obs.	3,181	1,823	14,489	8,769
Bandwidth Values	0.020	0.011	0.109	0.109
Kernel Function	Triangular	Triangular	Triangular	Triangular
Conventional p-value	0.377		0.257	
Robust est. p-value	0.140		0.996	

Table 2 Descriptive statistics

This table presents descriptive statistics for the key variables. The sample period ranges from 2004 to 2017 for the main analyses. The sample period for Patents ($Patents_{t+1,\, t+3}$) and Citations ($Patents_{t+1,\, t+3}$) analyses is between 2004 and 2009. The sample period for Merger and Acquisition ($M\&A_{t+1}$) analysis is between 2004 and 2015. Variables used in cross-sectional analyses are presented as continuous variables. All continuous variables are winsorized at 1% and 99%. Appendix A provides variable descriptions.

	N	Mean	Stdev	25th	50th	75th
Main variables						
BTM_t	108,080	0.719	0.431	0.409	0.712	0.972
$Impairment\ Indicator_t$	108,080	0.178	0.382	0.000	0.000	0.000
$Impairments_t$	100,426	0.015	0.071	0.000	0.000	0.000
$R\&D_{t+1}$	41,571	0.069	0.120	0.002	0.026	0.082
$CAPX_{t+1}$	91,498	0.076	0.155	0.005	0.021	0.073
$Patents_{t+1,\, t+3}$	41,978	2.850	42.875	0	0	0
$Citation_{t+1,\, t+3}$	41,978	0.636	9.566	0	0	0
$M\&A_{t+1}$	89,207	0.090	0.286	0	0	0
$Missing\ R\&D_{t+1}$	49,650	0.069	0.253	0	0	0
Variables in cross-sectional tests						
$New\ External\ Financing_t$	103,289	-0.109	1.240	-0.106	-0.010	0.089
$Relative\ Sales\ Growth_t$	103,126	0.073	0.332	-0.008	0.013	0.117
$Firm\ Age_t$	108,078	16.638	13.911	6.000	12.000	22.000
$Audit\ Industry\ Expertise_t$	71,807	0.015	0.038	0.000	0.001	0.010
$Big\ N\ Auditor_t$	71,807	0.615	0.487	0.000	1.000	1.000
$Audit\ Fees_t$	73,624	13.167	1.639	11.995	13.278	14.280
$Firm\ Size_t$	108,080	6,011	23,664	35	306	1,858
Other Firm Characteristics						
ROA_t	106,289	-0.467	2.274	-0.098	0.011	0.059
$Leverage_t$	107,377	0.170	0.242	0.000	0.067	0.261

Table 3 Kink effects on asset impairments

This table examines whether the impairment loss recognition in period *t* exhibits a kink at the book-to-market ratio equal to 1 in period *t*. Panel A examines the kink effects of the probability of impairment loss recognition. Panel B examines the kink effects of the amount of asset impairments. We compare the slope estimated from samples lying on the right-hand side of the cutoff point and the slope estimated from those lying on the left-hand side of the cutoff point. In Panel A, the dependent variable is the indicator variable of goodwill impairment or long-lived asset impairment recognition in period *t* ($Impairment\ Indicator_t$). In Panel B, the dependent variable is the total amount of the goodwill impairments and the long-lived asset impairments in period *t* ($Impairments_t$). The independent variable is the book-to-market ratio in period *t* (BTM_t). Column 1 estimates kink effects using the local linear model, i.e., polynomial order = 1. Column 2 estimates kink effects using the local quadratic model, i.e., polynomial order = 2. The bandwidth and the estimated kink effects are optimally calculated following Calonico et al. (2014) and Calonico et al. (2016). The dependent variables are winsorized at 1% and 99%. Standard errors are adjusted for heteroscedasticity and three nearest neighbor observations. Appendix A provides detailed variable descriptions.

Panel A The probability of impairment loss recognition

	Local Linear Model	Local Quadratic Model
	Indicator var. of Asset Impairments	Indicator var. of Asset Impairments
	(1)	(2)
Estimation		
Estimated Kink	1.4351***	1.9459***
Std. Error	0.238	0.270
P-value	0.000	0.000
Left of Cutoff (BTM = 1)		
Bandwidth	0.093	0.229
Eff. Number of Obs.	12,779	25,885
Right of Cutoff (BTM = 1)		
Bandwidth	0.093	0.229
Eff. Number of Obs.	9,554	14,003
Kernel Function	Triangular	Triangular

Panel B The amount of impairment loss recognition

	Local Linear Model	Local Quadratic Model
	Asset Impairments	Asset Impairments
	(1)	(2)
Estimation		
Estimated Kink	0.3833***	0.4919***
Std. Error	0.038	0.067
P-value	0.000	0.000
Left of Cutoff (BTM = 1)		
Bandwidth	0.115	0.195
Eff. Number of Obs.	14,357	21,506
Right of Cutoff (BTM = 1)		
Bandwidth	0.115	0.195
Eff. Number of Obs.	9,881	12,472
Kernel Function	Triangular	Triangular

Table 4 Kink effects on investments in innovation and capital expenditures

This table examines whether R&D in period *t+1* ($R\&D_{t+1}$) or capital expenditure in period *t+1* ($CAPX_{t+1}$) exhibit a kink at the book-to-market ratio (BTM_t) equal to 1 in period *t*. We compare the slope estimated from samples lying on the right-hand side of the cutoff point and the slope estimated from those lying on the left-hand side of the cutoff point. The dependent variable in Panel A (Panel B) is $R\&D_{t+1}$ ($CAPX_{t+1}$). The bandwidth and the estimated kink effects are optimally calculated following Calonico et al. (2014) and Calonico et al. (2016). The dependent variables are winsorized at 1% and 99%. Standard errors are adjusted for heteroscedasticity and three nearest neighbor observations. Appendix A provides detailed variable descriptions.

Panel A R&D expenditures

	$R\&D_{t+1}$
Estimation	
Estimated Kink	0.2006***
Std. Error	0.047
P-value	0.000
Left of Cutoff (BTM = 1)	
Bandwidth	0.250
Eff. Number of Obs.	7,722
Right of Cutoff (BTM = 1)	
Bandwidth	0.250
Eff. Number of Obs.	3,304
Kernel Function	Triangular

Panel B Capital expenditures

	$CAPX_{t+1}$
Estimation	
Estimated Kink	0.7807***
Std. Error	0.129
P-value	0.000
Left of Cutoff (BTM = 1)	
Bandwidth	0.084
Eff. Number of Obs.	9,960
Right of Cutoff (BTM = 1)	
Bandwidth	0.084
Eff. Number of Obs.	7,700
Kernel Function	Triangular

Table 5 Cross-sectional analyses

This table examines the cross-sectional variation of the kink effects in $R\&D_{t+1}$ and $CAPX_{t+1}$ at the book-to-market ratio equal to 1 in period t (BTM_t). We examine cross-section variations depending on firm characteriscs (*New External Financing*$_t$, *Firm Size*$_t$, *Firm Age*$_t$, and *Relative Sales Growth*$_t$) and audit characteristics (*Big N Auditor*$_t$, *Auditor Industry Expertise*$_t$, and *Audit Fees*$_t$). We compare the slope estimated from samples lying on the right-hand side of the cutoff point and the slope estimated from those lying on the left-hand side of the cutoff point. The bandwidth and the estimated kink effects are optimally calculated following Calonico et al. (2014) and Calonico et al. (2016). The dependent variables are winsorized at 1% and 99%. Standard errors are adjusted for heteroscedasticity and three nearest neighbor observations. Appendix A provides detailed variable descriptions.

Panel A External financing

	High new external financing		Low new external financing	
	$R\&D_{t+1}$	$CAPX_{t+1}$	$R\&D_{t+1}$	$CAPX_{t+1}$
	(1)	(2)	(4)	(5)
Estimation				
Estimated Kink	0.3302***	0.9334***	0.1247**	0.7897***
Std. Error	0.105	0.154	0.049	0.129
P-value	0.002	0.000	0.012	0.000
Left of Cutoff (BTM = 1)				
Bandwidth	0.180	0.096	0.302	0.113
Eff. Number of Obs.	2,631	6,008	4,953	5,887
Right of Cutoff (BTM = 1)				
Bandwidth	0.180	0.096	0.302	0.113
Eff. Number of Obs.	1,581	4,534	1,510	3,944
Kernel Function	Triangular	Triangular	Triangular	Triangular

Panel B Firm size

	Large firms		Small firms	
	$R\&D_{t+1}$	$CAPX_{t+1}$	$R\&D_{t+1}$	$CAPX_{t+1}$
	(1)	(2)	(4)	(5)
Estimation				
Estimated Kink	0.1392***	1.180***	0.0784*	0.3804***
Std. Error	0.024	0.146	0.042	0.090
P-value	0.000	0.000	0.067	0.000
Left of Cutoff (BTM = 1)				
Bandwidth	0.638	0.089	0.428	0.183
Eff. Number of Obs.	13,952	8,010	5,877	4,912
Right of Cutoff (BTM = 1)				
Bandwidth	0.638	0.089	0.428	0.183
Eff. Number of Obs.	2,060	5,459	2,216	3,901
Kernel Function	Triangular	Triangular	Triangular	Triangular

Panel C Firm age

	Old firms		Young firms	
	R&D$_{t+1}$	*CAPX*$_{t+1}$	*R&D*$_{t+1}$	*CAPX*$_{t+1}$
	(1)	(2)	(4)	(5)
Estimation				
Estimated Kink	0.0348	0.6514***	0.3767***	0.8934***
Std. Error	0.025	0.129	0.066	0.135
P-value	0.168	0.000	0.000	0.000
Left of Cutoff (BTM = 1)				
Bandwidth	0.691	0.117	0.263	0.104
Eff. Number of Obs.	12,612	5,516	4,377	7,105
Right of Cutoff (BTM = 1)				
Bandwidth	0.691	0.117	0.263	0.104
Eff. Number of Obs.	1,938	3,188	1,885	5,550
Kernel Function	Triangular	Triangular	Triangular	Triangular

Panel D Firm sales growth relative to industry sales growth

	Firm sales growth > Industry sales growth		Firm sales growth < Industry sales growth	
	R&D$_{t+1}$	*CAPX*$_{t+1}$	*R&D*$_{t+1}$	*CAPX*$_{t+1}$
	(1)	(2)	(4)	(5)
Estimation				
Estimated Kink	0.0969	0.8725***	0.4074***	0.8779***
Std. Error	0.060	0.151	0.113	0.145
P-value	0.108	0.000	0.000	0.000
Left of Cutoff (BTM = 1)				
Bandwidth	0.288	0.106	0.166	0.097
Eff. Number of Obs.	4,264	5,964	2,634	5,636
Right of Cutoff (BTM = 1)				
Bandwidth	0.288	0.106	0.166	0.097
Eff. Number of Obs.	1,296	2,972	1,640	5,384
Kernel Function	Triangular	Triangular	Triangular	Triangular

Panel E Big N auditors vs. non-Big N auditors

	Big N auditors		Non-Big N auditors	
	$R\&D_{t+1}$	$CAPX_{t+1}$	$R\&D_{t+1}$	$CAPX_{t+1}$
	(1)	(2)	(4)	(5)
Estimation				
Estimated Kink	0.4221***	0.9492***	0.1020***	0.5563***
Std. Error	0.119	0.160	0.023	0.105
P-value	0.000	0.000	0.000	0.000
Left of Cutoff (BTM = 1)				
Bandwidth	0.152	0.110	0.924	0.133
Eff. Number of Obs.	2,367	5,673	8,203	3,939
Right of Cutoff (BTM = 1)				
Bandwidth	0.152	0.110	0.924	0.133
Eff. Number of Obs.	1,246	3,278	1,561	3,052
Kernel Function	Triangular	Triangular	Triangular	Triangular

Panel F Audit industry expertise

	High industry expertise		Low industry expertise	
	$R\&D_{t+1}$	$CAPX_{t+1}$	$R\&D_{t+1}$	$CAPX_{t+1}$
	(1)	(2)	(4)	(5)
Estimation				
Estimated Kink	0.2964***	0.9701***	0.1050***	0.6704***
Std. Error	0.089	0.195	0.033	0.112
P-value	0.001	0.000	0.002	0.000
Left of Cutoff (BTM = 1)				
Bandwidth	0.188	0.110	0.462	0.100
Eff. Number of Obs.	2,682	4,353	8,061	7,465
Right of Cutoff (BTM = 1)				
Bandwidth	0.188	0.110	0.462	0.100
Eff. Number of Obs.	1,240	2,745	2,555	5,724
Kernel Function	Triangular	Triangular	Triangular	Triangular

Panel G Audit fees

	High audit fees		Low audit fees	
	R&D$_{t+1}$	*CAPX*$_{t+1}$	*R&D*$_{t+1}$	*CAPX*$_{t+1}$
	(1)	(2)	(4)	(5)
Estimation				
Estimated Kink	0.2637***	1.0553***	0.1333***	0.6848***
Std. Error	0.083	0.193	0.023	0.116
P-value	0.001	0.000	0.000	0.000
Left of Cutoff (BTM = 1)				
Bandwidth	0.198	0.103	0.641	0.102
Eff. Number of Obs.	2,919	4,784	11,645	6,894
Right of Cutoff (BTM = 1)				
Bandwidth	0.198	0.103	0.641	0.102
Eff. Number of Obs.	1,234	2,796	2,914	5,636
Kernel Function	Triangular	Triangular	Triangular	Triangular

Table 6 Kink effects on M&A activities

This table examines whether M&A activities in period *t+1* exhibit kink at the book-to-market ratio equal to 1 in period *t*. The dependent variable is the indicator variable equal to 1 if M&A activities occur in period *t+1* ($M\&A_{t+1}$). The independent variable is the book-to-market ratio in period *t* (BTM_t). Column 1 demonstrates a kink effect on M&A activities in period *t+1* using the full sample. Column 2 presents estimation results using a sub-sample with positive goodwill in period *t*. We compare the slope estimated from samples lying on the right-hand side of the cutoff point and the slope estimated from those lying on the left-hand side of the cutoff point. The bandwidth and the estimated kink effects are optimally calculated following Calonico et al. (2014) and Calonico et al. (2016). The sample period is from 2004 to 2014. The dependent variables are winsorized at 1% and 99%. Standard errors are adjusted for heteroscedasticity and three nearest neighbor observations. Appendix A provides detailed variable descriptions.

	$M\&A_{t+1}$	
	(1)	(2)
	Full Sample	Sample with Goodwill > 0
Estimation		
Estimated Kink	-0.0811*	-0.2288**
Std. Error	0.047	0.107
P-value	0.086	0.033
Left of Cutoff (BTM = 1)		
Bandwidth	0.269	0.202
Eff. Number of Obs.	24,385	11,239
Right of Cutoff (BTM = 1)		
Bandwidth	0.269	0.202
Eff. Number of Obs.	12,518	5,360
Kernel Function	Triangular	Triangular

Table 7 Kink effects on patenting activities

This table examines whether patents filed between period *t+1* and period *t+3* exhibit kink at the book-to-market ratio equal to 1 in period *t*. In Panel A, the dependent variable is the natural log of the number of patents filed between period *t+1* and period *t+3* ($Patents_{t+1,\ t+3}$). In Panel B, the dependent variable is the quality of the patent, which is defined as the natural log of the average per-year citation of patents filed between period *t+1* and period *t+3* ($Citation_{t+1,\ t+3}$). We compare the slope estimated from samples lying on the right-hand side of the cutoff point and the slope estimated from those lying on the left-hand side of the cutoff point. The independent variable is the book-to-market ratio in period *t* (BTM_t). The bandwidth and the estimated kink effects are optimally calculated following Calonico et al. (2014) and Calonico et al. (2016). The sample period is from 2004 to 2008. The dependent variables are winsorized at 1% and 99%. Standard errors are adjusted for heteroscedasticity and three nearest neighbor observations. Appendix A provides detailed variable descriptions.

Panel A The number of patents

	$Patents_{t+1,\ t+3}$
Estimation	
Estimated Kink	0.6004***
Std. Error	0.0902
P-value	0.000
Left of Cutoff (BTM = 1)	
Bandwidth	0.402
Eff. Number of Obs.	17415
Right of Cutoff (BTM = 1)	
Bandwidth	0.402
Eff. Number of Obs.	5272
Kernel Function	Triangular

Panel B The number of citations

	$Citation_{t+1,\ t+3}$
Estimation	
Estimated Kink	0.2351**
Std. Error	0.0641
P-value	0.000
Left of Cutoff (BTM = 1)	
Bandwidth	0.365
Eff. Number of Obs.	16005
Right of Cutoff (BTM = 1)	
Bandwidth	0.365
Eff. Number of Obs.	5090
Kernel Function	Triangular

Table 8 Kink effects on R&D and M&A activities in the pre-SFAS 142 period

This table examines whether R&D and M&A in period *t+1* exhibit kink at the book-to-market ratio equal to 1 in period *t* in the pre-SFAS 142 period between 1996 and 2001. We compare the slope estimated from samples lying on the right-hand side of the cutoff point and the slope estimated from those lying on the left-hand side of the cutoff point. In Column 1, the dependent variable is R&D expenditures in period *t+1* ($R\&D_{t+1}$). In Column 2, the dependent variable is an indicator of the M&A activities in period *t+1* ($M\&A_{t+1}$). The independent variable is the book-to-market ratio in period *t* (BTM_t). The bandwidth and the estimated kink effects are optimally calculated following Calonico et al. (2014) and Calonico et al. (2016). The dependent variables are winsorized at 1% and 99%. Standard errors are adjusted for heteroscedasticity and three nearest neighbor observations. Appendix A provides detailed variable descriptions.

	$R\&D_{t+1}$	$M\&A_{t+1}$
	(1)	(2)
Estimation		
Estimated Kink	0.0428	-0.0176
Std. Error	0.044	0.109
P-value	0.334	0.872
Left of Cutoff (BTM = 1)		
Bandwidth	0.293	0.248
Eff. Number of Obs.	5,669	5,739
Right of Cutoff (BTM = 1)		
Bandwidth	0.293	0.248
Eff. Number of Obs.	2,669	2,806
Kernel Function	Triangular	Triangular

Table 9 RKD estimation based on ad hoc bandwidths

This table reports two robustness tests on whether our findings are sensitive to the choices of cutoff points and bandwidths. Panel A uses the Local Linear Model (Polynomial order equal to 1, cutoff point equal to 1) and presents the kink estimation as ad hoc bandwidth changes from 0.06 to 0.25. We use a polynomial order of 1 and cutoff point BTM equal to 1. Then, we change the bandwidth from 0.06 to 0.25. Panel B uses the Local Linear Model (Polynomial order =1, a bandwidth of both left and right window 0.1 for *Impairment Indicator*$_t$, *Impairments*$_t$, and *R&D*$_{t+1}$, and a bandwidth of both left and right window 0.15 for *M&A*$_{t+1}$) and presents the kink estimation as the cutoff point moves away from the original cutoff point where BTM is equal to 1. We use a polynomial order of 1. Using increments of 0.1, we test different cutoff points between 0.7 and 1.3. P-values are in parenthesis. The continuous dependent variables (*Impairments*$_t$ *and R&D*$_{t+1}$) are winsorized at 1% and 99%. Appendix A provides detailed variable descriptions.

Panel A Ad hoc bandwidths

Bandwidth	*Impairment Indicator*$_t$	*Impairments*$_t$	*R&D*$_{t+1}$	*M&A*$_{t+1}$
(1)	(2)	(3)	(4)	(5)
0.06	0.9909**	0.2827*	0.0804	0.5738
	(0.015)	(0.060)	(0.819)	(0.251)
0.07	1.0929**	0.3163**	0.2060	0.1133
	(0.001)	(0.000)	(0.471)	(0.782)
0.08	1.2542***	0.3648***	0.2308	-0.1787
	(0.000)	(0.000)	(0.329)	(0.603)
0.09	1.3976***	0.3902***	0.2882	-0.2945
	(0.000)	(0.000)	(0.147)	(0.319)
0.1	1.512***	0.3946***	0.3243*	-0.3431
	(1.512)	(0.000)	(0.059)	(0.184)
0.11	1.5615***	0.3882***	0.3358**	-0.3507
	(0.000)	(0.000)	(0.026)	(0.127)
0.12	1.6104***	0.3787***	0.3272**	-0.3574*
	(0.000)	(0.000)	(0.015)	(0.084)
0.13	1.6277***	0.3647***	0.3167***	-0.3605*
	(0.000)	(0.000)	(0.008)	(0.054)
0.14	1.6242***	0.3436***	0.2991***	-0.3433**
	(0.000)	(0.000)	(0.005)	(0.044)
0.2	1.5267***	0.2737***	0.2298***	-0.2320**
	(0.000)	(0.000)	(0.000)	(0.033)
0.25	1.358***	0.2246***	0.2007***	-0.1960**
	(0.000)	(0.000)	(0.000)	(0.016)

Panel B Ad hoc cutoff points

Cutoff Point	*Impairment Indicator$_t$*	*Impairments$_t$*	*R&D$_{t+1}$*	*M&A$_{t+1}$*
(1)	(2)	(3)	(4)	(5)
0.7	0.0457	0.0176	-0.0578	-0.0923
	(0.854)	(0.582)	(0.604)	(0.591)
0.8	-0.4492*	0.0245	0.1415	0.1059
	(0.076)	(0.460)	(0.220)	(0.515)
0.9	0.1494	-0.0084	-0.0135	-0.1058
	(0.504)	(0.808)	(0.918)	(0.493)
1	1.512***	0.3946***	0.3243*	-0.3249**
	(0.000)	(0.000)	(0.059)	(0.038)
1.1	-1.2453***	-0.2486**	-0.2458	0.4705**
	(0.002)	(0.014)	(0.304)	(0.015)
1.2	-0.5606	0.1124	-0.5556	0.1631
	(0.304)	(0.425)	(0.106)	(0.505)
1.3	0.4503	0.0221	-0.3317	-0.0695
	(0.506)	(0.914)	(0.446)	(0.838)

Table 10 Kink effects on missing R&D disclosure

This table examines whether disclosure of missing R&D in period *t+1* exhibit a kink at the book-to-market ratio equal to 1 in period *t*. We compare the slope estimated from samples lying on the right-hand side of the cutoff point and the slope estimated from those lying on the left-hand side of the cutoff point. The dependent variable is *Missing* $R\&D_{t+1}$, and the independent variable is the book-to-market ratio in period *t* (BTM_t). The bandwidth and the estimated kink effects are optimally calculated following Calonico et al. (2014) and Calonico et al. (2016). The sample period is from 2004 to 2009. Standard errors are adjusted for heteroscedasticity and three nearest neighbor observations. Appendix A provides detailed variable descriptions.

	Missing $R\&D_{t+1}$
Estimation	
Estimated Kink	0.3545***
Std. Error	0.123
P-value	0.004
Left of Cutoff (BTM = 1)	
Bandwidth	0.160
Eff. Number of Obs.	9,323
Right of Cutoff (BTM = 1)	
Bandwidth	0.160
Eff. Number of Obs.	4,795
Kernel Function	Triangular

Table 11 Kink effects on audit fees

This table examines whether audit fees in period *t* exhibit a kink at the book-to-market ratio equal to 1 in period *t*. We compare the slope estimated from samples lying on the right-hand side of the cutoff point and the slope estimated from those lying on the left-hand side of the cutoff point. The dependent variable is the natural log of audit fees in period *t* ($Audit\ Fees_t$). The independent variable is the book-to-market ratio in period *t* (BTM_t). The bandwidth and the estimated kink effects are optimally calculated following Calonico et al. (2014) and Calonico et al. (2016). The dependent variable is winsorized at 1% and 99%. Standard errors are adjusted for heteroscedasticity and three nearest neighbor observations. Appendix A provides detailed variable descriptions.

	$Audit\ Fees_t$
	(1)
Estimation	
Estimated Kink	2.857***
Std. Error	0.811
P-value	0.000
Left of Cutoff (BTM = 1)	
Bandwidth	0.128
Eff. Number of Obs.	11,678
Right of Cutoff (BTM = 1)	
Bandwidth	0.128
Eff. Number of Obs.	7,279
Kernel Function	Triangular