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The Real Effects of Real Earnings Management: Evidence from Innovation*

FREDERICK L. BERESKIN, University of Delaware
PO-HSUAN HSU, University of Hong Kong
WENDY ROTENBERG, University of Toronto†

Abstract

We examine the consequences of real earnings management from an innovation perspective and investigate the patent output of firms likely to be managing earnings through altering their R&D expenditures. We find that R&D cuts related to earnings management lead to fewer patents, less influential patent output, and lower innovative efficiency compared to other R&D cuts. Our results thus suggest that real earnings management may obstruct firms' technological progress and highlight the potential costs of managerial manipulation of R&D expenditures in order to alter reported earnings.

Keywords: Earnings management, real activity manipulation, patents, innovation

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† Corresponding author: rotenber@rotman.utoronto.ca

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Les véritables conséquences de la gestion du résultat réel :
données relatives à l'innovation

Frederick L. Bereskin, Po-Hsuan Hsu et Wendy Rotenberg

Résumé

Les auteurs se penchent sur les conséquences de la gestion du résultat réel dans la perspective de l'innovation et s'interrogent sur les extrants brevetés de sociétés susceptibles de se livrer à la gestion du résultat en modifiant leurs dépenses de R&D. Ils constatent que les réductions des dépenses de R&D motivées par la gestion du résultat mènent à un moins grand nombre de brevets, à des extrants brevetés de moins grande portée et à une efficience plus faible au chapitre de l'innovation que les réductions motivées par d'autres facteurs. Ces observations semblent donc indiquer que la gestion du résultat réel peut faire obstacle au progrès technologique des sociétés et mettent en lumière les coûts potentiels de la manipulation des dépenses de R&D par la direction dans le but de modifier les résultats qu'elle communique.

Mots clés : brevets, gestion du résultat, innovation, manipulation des activités réelles

Classification JEL :

1. Introduction

The reliance of external stakeholders on reported accounting information creates incentives for firms to report earnings that meet or exceed targets and forecasts.[1] According to Graham et al. (2005), CFOs believe that reported earnings, rather than cash flows, are the primary metric used by external stakeholders to assess the value of the firm. These beliefs may lead to the management of reported results in order to enhance the firm's reputation with external parties. The tools to do so involve engaging in potentially value-reducing actions to boost short-term reported performance. The presence of such behavior is corroborated by a wealth of evidence indicating that firms take actions such as selling assets and reducing discretionary expenditures in order to manage reported earnings (Dechow and Sloan 1991; Bartov 1993; Bushee 1998; Roychowdhury 2006; Mizik and Jacobson 2007; Gunny 2010). In Graham et al. (2005), the most frequently cited mechanism to achieve reported earnings benchmarks is the reduction of discretionary spending.

An alternative to managing reported earnings via changes in real activities is to do so by altering accounting accruals. There is well-documented evidence of substitution between these two types of earnings management strategies (e.g., Cohen et al. 2008; Cohen and Zarowin 2010; Badertscher 2011; Zang 2012). Accrual-based earnings management is short-lived and has subsequent reversals. In contrast, changes in real activities to manage short-term reported performance by definition involve suboptimal managerial decisions with potentially adverse consequences. In the surveys of Bruns and Merchant (1990) and Graham et al. (2005), managers indicate a *greater* willingness to use real activities rather than accruals to manipulate reported earnings. Roychowdhury (2006) argues that this preference for real activities manipulation,

[1] See, for example, Burstahler and Dichev (1997).

despite the potentially greater long-term costs to the company, may arise because managers expect to bear greater private costs if they engage in accruals manipulation.

Real changes made to manage earnings upwards involve such actions as increasing inventory production to reduce reported cost of goods sold, timing asset sales opportunistically, and reducing discretionary spending on items such as R&D, advertising, and maintenance.[2] Real earnings management (hereafter REM) is considered to be more difficult to control than accrual-based earnings management (Dichev et al. 2013), as it is an operational decision rather than an accrual estimate that is subject to auditor scrutiny. This notion is demonstrated analytically in the Ewert and Wagenhofer (2005) model in which tighter accounting standards make accruals management more difficult, resulting in greater REM. Consistent with this framework, Cohen et al. (2008) report an increase in the use of REM following the Sarbanes-Oxley Act, as this regulation curbed accruals management.

Despite the prevalence of REM, there are few studies examining its consequences. To further examine the real effects of real activities manipulation, we focus on the change in a discretionary input measure—R&D expenses—and on the associated effect on subsequent innovation output measured with patents. Patents provide intellectual property protection, are proprietary in nature, and are shown from prior research to be value-relevant.[3] The benefit of examining R&D expenditures is that, to the degree that R&D is closely related to innovation output that can be appropriately measured using patent data, we are able to study the subsequent

[2] A number of studies examine the role of managerial intervention on the level of R&D expenditures, including Baber et al. (1991), Dechow and Sloan (1991), Bushee (1998), Bens et al. (2002), Cheng (2004), and Kothari et al. (2016). Other examples of real earnings management include managerial decisions such as asset sales (Bartov 1993) and reducing advertising expenses (Cohen et al. 2010).
[3] Patents have been actively traded in intellectual property markets (Lev 2001) and serve as collateral for secured credit (Mann 2017). Several recent studies provide empirical evidence of the positive impact of disclosed patent activities on firm performance and financing opportunities, including Gunny and Zhang (2014), Hsu et al. (2015), Plumlee et al. (2015), and Chava et al. (2016).

output effect from a decision related to an earnings management *input*.[4] Another reason for examining R&D expenses and patents is that we are studying items that are critical for a firm's future competitive advantage and long-term survival in today's knowledge economy.

When cuts to R&D are motivated by reported earnings considerations, they should by definition be more costly than those driven by operational goals. Thus, we would expect a deeper drop in patent output after REM-related R&D cuts in comparison with operational cuts. Alternatively, there may be other effects that offset the negative impacts of REM-related R&D cuts. In particular, REM may force managers to divest unnecessary or even wasteful projects. For instance, Jensen (1993) and Hall (1993) argue that R&D could be subject to executives' empire-building ambitions and be reflective of their overoptimism. Managers may also pursue certain "pet" projects that serve only to increase their own private benefits, such as enhancing their social image and self-esteem (Almeida et al. 2013). This sort of behavior would be consistent with aggregate-level evidence in Jaffe (2000) and Lanjouw and Schankerman (2004) indicating that the substantial increase in total R&D investment since the 1980s has not led to commensurate changes in total patent output. If managers focused on meeting performance benchmarks are actually cutting unnecessary R&D projects, this would not harm firms' innovation performance.

To test our hypothesis, we construct a data set consisting of the innovation and financial data of all U.S. public firms that have R&D expenditures between 1987 and 2014. Our empirical

[4] By linking a real activities manipulation input with a closely associated output, our paper follows from Cohen et al. (2010) and Chapman and Steenburgh (2011), who examine advertising and marketing actions, and Gupta et al. (2010), who examine overproduction and accounting performance. Given the broader literature on the consequences of real activities manipulation (e.g., Bhojraj et al. 2009; Gunny 2010), we focus on a particular manifestation and associated consequence to provide new insights about REM. While it is possible that some firms engage in innovative activities without reporting R&D expense (Koh and Reeb 2015), these situations will not be captured in our tests.

design builds on the Roychowdhury (2006) and Gunny (2010) frameworks to distinguish earnings-management related cuts to R&D from other cuts. In particular, we distinguish between earnings-management related cuts to R&D and all other abnormal R&D cuts. Earnings-management related cuts to R&D are based on a benchmark of meeting or narrowly beating the prior year's level of ROA, defined as income before extraordinary items scaled by total assets. A firm with a change in ROA greater than or equal to zero and less than 1 percent would have its abnormal cut to R&D classified as REM-related (Gunny 2010). We drop firms with negative changes in ROA due to the endogeneity of poorly performing firms cutting R&D expenses for operational reasons instead of REM. In robustness tests, we also consider alternative earnings benchmarks suggested in prior studies (such as meeting or narrowly beating analyst forecasts or positive ROA), and we use different approaches to identify earnings-management related cuts to R&D.

To evaluate the innovation profile of our sample firms, we construct empirical measures of firms' innovation performance in time windows of one, two, or three years. We construct our measures for innovation performance using the data on patents granted by the United States Patent and Trademark Office (USPTO).[5] Our first innovation measure is the number of patents filed by the focal firm in a time window and approved by the USPTO by the end of our sample period ("patent counts"; see Scherer 1965 and Griliches 1981). Our second innovation measure is the number of forward citations received by these patents ("patent citations"; see Hall et al. 2005a; Pandit et al. 2011). Finally, our third measure is the log-linearized number of patents per R&D expenditure ("innovative efficiency"; see Lanjouw and Schankerman 2004; Cohen et al.

[5] Patents are often regarded as the best information source currently available to researchers for measuring innovation performance. Lev (1999, 32) notes that "Research capability should be assessed primarily by output measures, such as the number of new products that have emerged from the development process, as well as the number of patents, patent citations, and trademarks registered."

2013; Hirshleifer et al. 2013). These measures are frequently used in the literature and reflect how successfully a firm innovates, both in terms of the quantity and quality of its innovative output, as well as how efficiently its R&D investments are converted into future innovations.

Our results suggest that there are significant negative consequences associated with declines in R&D expenditures when driven by earnings-management concerns and that the decline is more severe than for other cuts to R&D. To evaluate the economic effects of our findings, we calculate the change in the fitted value of innovation for a one standard deviation increase in REM-related cuts to R&D. In particular, a one standard deviation increase in REM-related R&D spending cuts is associated with a 2.9 percent decline in the number of patents, a 3.9 percent decline in patent citations, and a 36.0 percent decline in innovative efficiency in the subsequent three-year period. To the degree that innovation is a critical determinant of firms' long-run success, our results thus suggest that REM-related declines in innovative output can severely impact a firm's future development and competitiveness.

To address the endogeneity issue related to reduced innovation opportunities, we consider the following approaches: First, throughout our analyses, we control for firm-specific innovation opportunities using the intensity of patenting activities of universities in the same technology areas as the sample firm.[6] Second, we employ a matching methodology to construct a balanced sample of control firms that are similar to the treated firms (i.e., REM firms) in innovation opportunities. We obtain consistent results both ways. Nevertheless, we note that the above methods can only control for *observable* innovation opportunities and are unable to fully solve the *unobservable* omitted variable issue. Even if our results are driven by unobservable

[6] Since firms' innovations are mainly applied science and tend to follow the basic science created by universities (Jaffe 1989; Trajtenberg et al. 1997; Azoulay et al. 2007; Bereskin et al. 2016), the intensity of universities' patenting activities helps us to capture the innovation opportunities of the firm.

innovation opportunities, they can still be interpreted as offering evidence that REM-related R&D cuts are more likely to occur among firms with weaker innovation opportunities that are also close to missing earnings benchmarks.

We also provide an additional perspective on our results by examining innovative efficiency using patent counts and citations. We find that firms cutting R&D expenditures for REM purposes also perform less efficiently in innovation than do firms that cut R&D expenditures for other reasons. This represents possible evidence that managers engaging in REM are cutting the projects that are easiest to adjust instead of cutting less efficient investments. This finding is consistent with the presence of extra costs when engaging in real activities management, including contracting costs, division-level resistance to cuts, and managers' actions to obfuscate the extent of their earnings management.

To recap, we present empirical evidence of the real effects of REM from an innovation perspective. Our findings are consistent with REM-related adjustments to R&D expenditures having a significantly negative impact on their associated output (quantity, quality, and efficiency). These findings imply that to the degree that managers are incentivized to pursue myopic actions, such as cutting R&D expenditures to achieve earnings targets, they may sacrifice firms' future prospects and sustainable long-term competitive advantages. In addition, the approach used in our study is unique in examining the effects of REM because of the ability to measure R&D-related output using patent data.

The rest of our paper is organized as follows. In section 2, we review the literature and discuss our hypothesis in more detail. We continue in section 3 with a description of our data and sample. In section 4, we present our results on the relative effects of REM-related R&D cuts on innovative output, along with a variety of extensions and robustness tests. Concluding remarks follow in section 5.

2. Literature review and hypothesis development

In this section, we first review the REM literature and the associated effects on firms' operations observed in prior studies. This leads to our paper's focus: the effect of REM-related R&D cuts. We then discuss prior evidence of the value-relevance of firms' innovation activities, as this substantiates our rationale for investigating this important topic. Finally, we discuss our hypothesis regarding the influence of REM-related R&D cuts on subsequent innovation performance.

REM and consequences

REM refers to managerial decisions that affect corporate operations with the goal of presenting favorable financial results. REM has been found to be a common practice. In fact, as the surveys of Bruns and Merchant (1990) and Graham et al. (2005) suggest, financial executives prefer to manipulate earnings through altering discretionary spending rather than through accruals. Discretionary spending includes selling, general, and administrative expenses (SG&A), R&D expenses, and advertising expenses, and has been suggested in the literature as a mechanism for managing earnings (Schipper 1989; Baber et al. 1991; Fudenberg and Tirole 1995; Bushee 1998; Healy and Wahlen 1999; Dechow and Skinner 2000).[7]

[7] The prevalence of REM is primarily driven by the following three considerations: First, it is difficult for shareholders to control managerial discretionary spending (Dichev et al. 2013); second, some REM activities can enhance managers' private benefits (Dechow and Sloan 1991; Matsunaga and Park 2001; Bens et al. 2002); and

Perhaps because of measurement difficulties, the *consequences* of REM have so far received little attention in the literature. While REM predicts weaker operating performance (as by definition these cuts would not have occurred absent reporting incentives), it is possible that REM leads management to discontinue pet projects, in which case future earnings would *not* suffer. Consistent with the role of reporting incentives, Cohen and Zarowin (2010) show that firm underperformance following seasoned equity offerings (SEOs) is driven in part by the effects of earnings management-related operational decisions. They also report that these REM effects are more severe than are the effects driven by accrual-based earnings management.

The effects of REM remain underexplored in the literature. As firms operating in today's knowledge-based economy face fierce technological competition, their investment and performance in innovation may be particularly important for their market power and long-term sustainability. We are thus motivated to investigate the influence of REM on corporate performance from an innovation perspective.

Value-relevance of innovation activities

Evidence from numerous empirical studies suggests that firms with larger R&D expenditures exhibit better operating performance and profitability. For example, Lev and Sougiannis (1996), Chan et al. (2001), Kothari et al. (2002), and Eberhart et al. (2004) report that R&D-intensive firms enjoy stronger future profitability and operating performance.[8] The positive link between innovative activities and corporate performance is thus well established.

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third, the tightening of accounting standards has made accrual-based earnings management more difficult (Ewert and Wagenhofer 2005; Cohen et al. 2008).

[8] At the aggregate level, Hobijn and Jovanovic (2001), Pástor and Veronesi (2009), and Hsu (2009) have presented evidence for the positive relation between technological innovation and stock market capitalization. Similarly, Terry (2015) shows the negative effects on growth of meeting earnings targets by cutting R&D expenditures.

After controlling for R&D intensity, researchers also report findings suggesting that patents predict future operating performance and profitability. For instance, Gu (2005) and Pandit et al. (2011) show that firms with stronger patent portfolios report better profitability and operating performance. Similarly, researchers have documented that firms with better patent performance are associated with higher market valuation (Griliches 1990; Deng et al. 1999; Lerner 1994; Lanjouw and Schankerman 2004) and subsequent stock returns (Gu 2005; Cohen et al. 2013; Hirshleifer et al. 2013, 2017). Overall, prior studies collectively suggest strong, positive effects of corporate innovation activities on operating performance, profitability, and market value.

Hypothesis development

The occurrence of REM could suggest poor corporate governance and the presence of agency issues, which can be harmful to corporate performance.[9] Since U.S. generally accepted accounting principles (GAAP) require R&D expenditures to be expensed immediately in most cases, R&D investments directly impact reported earnings and are therefore prone to being managed for reporting purposes. This behavior may be myopic with detrimental long-run effects, in that it can lead managers to underinvest in R&D in order to boost reported performance (Baber et al. 1991; Dechow and Sloan 1991; Bushee 1998; Acharya and Xu 2017). Moreover, R&D investments are particularly subject to information asymmetries due to their inherent complexity and uncertainty (e.g., Hall and Lerner 2010; Seru 2014). This can be especially problematic when agency issues are a concern. Prior studies that have reported relationships between agency issues and R&D expenditures include Aboody and Lev (2000), who find that

[9] Consistent with the negative effects of weak corporate governance on firm innovation, Cumming et al. (2016) and Levine et al. (2016) present evidence of market manipulation and insider trading opportunities, respectively, being negatively associated with firms' innovation performance.

R&D activities may be associated with insider trading gains, and Bens et al. (2002), who find that managers tend to divert funds from R&D and capital investments to stock repurchases when they exercise stock options, leading to weaker subsequent profitability.

Another implication of the aforementioned complexity associated with R&D investments is that decisions to cut R&D that are driven by reporting incentives might be made in some haste, and with less information than would be the case for carefully planned R&D cuts. Normally, we would expect that reductions in R&D expenditures would involve cuts to the least valuable projects. If instead R&D cuts are made with incomplete information, various frictions may prevent the cutting of the lowest NPV projects. The cuts may then have an especially adverse impact on innovation performance. We offer the following reasons why suboptimal R&D cuts may be made for reporting purposes. First, in contrast to accrual-based earnings management, REM has to be analyzed within the context that it must occur by the end of the fiscal year, even though the true effect on firms' earnings will not be known until after the end of the fiscal year (Zang 2012). In addition, contractual challenges (or other types of resistance among certain managers and divisions) may interfere with the ability to cut the least valuable R&D projects. An example would be the difficulties associated with adjusting the level of key personnel, who could be difficult to subsequently rehire (Himmelberg and Peterson 1994; Hall 2002).

The preceding discussion leads us to hypothesize the following:

> HYPOTHESIS. *REM-related R&D cuts lead to lower future innovative output in comparison with other R&D cuts.*

We note that there are some counter arguments to our hypothesis. For instance, some R&D expenditures may be driven by executives' empire-building ambitions and overoptimism

(Jensen 1993; Hall 1993). A common belief is that some research-intensive projects serve as CEOs' "pet" projects. These are used to increase the CEOs' private benefits, such as enhancing their social image and self-esteem (Almeida et al. 2013). As noted by *The Economist* (1990), "American industry went on an R&D spending spree, with few big successes to show for it." These studies and observations suggest that a portion of R&D expenditures may actually be unnecessary and may not convert particularly well into valuable patent output. When managers are under pressure to meet earnings benchmarks, they may therefore cut such unnecessary or even wasteful expenses without sacrificing future prospects of the firm. It is thus plausible that the REM cuts to R&D expenditures involve reductions in relatively unproductive R&D activities and that these R&D cuts could have little effect on valuable innovation activities. If this were the case, we would not obtain empirical results consistent with our hypothesis. Indeed, Curtis et al. (2016) report diminishing marginal returns to R&D investment, consistent with increased competition in innovative activities. Also, as suggested by Gunny (2010), meeting earnings benchmarks could signal the quality and confidence of managers to the market. These benefits could counteract the costs of abstaining from promising R&D activities. From these perspectives, R&D cuts driven by REM might not harm innovation performance.

3. Data and sample statistics

In this section, we construct empirical proxies for the extent of REM and technological innovation that will be used to examine the effect of REM on firms' innovative output.

Measures of REM

We first estimate a firm's "abnormal R&D cut" (Gunny 2010). We calculate abnormal R&D as the residual ($\varepsilon_{i,t}^{R\&D}$), estimated from the following regression:

$$\frac{RD_{i,t}}{A_{i,t-1}} = \alpha_0 + \alpha_1 \frac{1}{A_{i,t-1}} + \beta_1 MV_{i,t} + \beta_2 Q_{i,t} + \beta_3 \frac{INT_{i,t}}{A_{i,t-1}} + \beta_4 \frac{RD_{i,t-1}}{A_{i,t-1}} + \varepsilon_{i,t}^{R\&D}, \quad (1)$$

where $RD_{i,t}$ is the R&D expense of focal firm *i* in year *t*, $A_{i,t-1}$ is the total assets of focal firm *i* in year *t*–1, $MV_{i,t}$ is the natural log of focal firm *i*'s market value in year *t*, $Q_{i,t}$ is focal firm *i*'s Tobin's Q in year *t*, and $INT_{i,t}$ is the internal funds of focal firm *i* in year *t*.[10] Equation (1) is estimated for each year and industry (defined by SIC 2-digit codes), where there are at least 15 firms in the industry-year group. We note that the regression setup of Gunny (2010) does not include firm fixed effects, based on the rationale that all firms in the same industry and year are random draws from one population. The residual $\varepsilon_{i,t}^{R\&D}$ calculated in equation (1) measures abnormal R&D. A lower value indicates a deeper, unexpected cut in firm *i*'s R&D expense in year *t*. As we choose to focus on abnormal cuts to R&D, we only focus on cases where $\varepsilon_{i,t}^{R\&D}$ is negative, and define the following:

$$R\&DCut_{i,t} = -1 \times \varepsilon_{i,t}^{R\&D} \times Indicator\left(\varepsilon_{i,t}^{R\&D} < 0\right), \quad (2)$$

[10] Variable names are as defined in COMPUSTAT, as follows: R&D expense is variable XRD; total assets is variable AT; market value is the market value of equity (the product of shares outstanding and the stock price, or CSHO and PRCC_F); Tobin's Q is the market value of assets (the sum of the market value of equity CSHO×PRCC_F and book value of assets AT, less the book value of common equity CEQ and deferred taxes TXDB) scaled by the book value of assets (AT); and internal funds is the sum of income before extraordinary items (IB), depreciation and amortization (DP), and R&D expense (XRD).

where $Indicator\left(\varepsilon_{i,t}^{R\&D} < 0\right)$ is an indicator function that equals one if $\varepsilon_{i,t}^{R\&D} < 0$, and zero otherwise. A higher value of $R\&DCut_{i,t}$ reflects a deeper, unexpected cut in firm *i*'s R&D expenditure in year *t*.

We focus on how REM affects innovation output through REM-driven cuts to R&D, but a firm's R&D reductions may also have other motivations, such as reduced innovation opportunities. To help identify R&D declines that are related to REM but not to other reasons, we categorize abnormal R&D cuts into those associated with meeting earnings benchmarks and those associated with all other R&D cuts. That is, we refer to $R\&DCut_{i,t}$ as $R\&DCut\_REM_{i,t}$ if the firm narrowly meets or beats an earnings benchmark, and we refer to $R\&DCut_{i,t}$ as $R\&DCut\_Other_{i,t}$ in all other cases.[11] Essentially, we separate $R\&DCut_{i,t}$ as follows:

$$R\&DCut_{i,t} = \begin{cases} R\&DCut\_REM_{i,t} \; if \; Benchmark = 1 \\ R\&DCut\_Other_{i,t} \; if \; Benchmark = 0 \end{cases}, \tag{3}$$

where $Benchmark$ refers to the event of matching earnings benchmarks, which is defined in our baseline results as the one-year change in ROA (ROA is defined as income before extraordinary items scaled by assets) being greater than or equal to zero and less than 1 percent. In robustness specifications, we also provide results with $Benchmark$ defined as either (i) analyst forecast error being greater than or equal to zero and less than 0.01 per share; or (ii) the level of ROA being greater than or equal to zero and less than 1 percent. Moreover, to more appropriately identify the effect of REM-driven cuts to R&D, we exclude firm-year observations that did not meet or beat the benchmark. For example, with $Benchmark$ defined based on the one-year

[11] We attribute the full amount of $R\&DCut_{i,t}$ to REM-related cuts because managers do not ex ante know the exact amount of R&D cuts to match the earnings benchmark and thus have an incentive to overcut R&D expenses. In a robustness check, we find consistent results when we measure $R\&DCut\_REM_{i,t}$ as the amount of R&D cuts necessary to meet the benchmark, and we attribute the rest of R&D cuts to $R\&DCut\_Other_{i,t}$.

change in ROA, we exclude firm-years with negative one-year change in ROA, as those observations' R&D cuts are less likely to have been driven by earnings management goals.[12] We also obtain consistent results when we include these firm-year observations in a robustness check.

Measures of innovation performance

In order to capture firms' innovation performance after experiencing REM-related R&D cuts, we exploit firm-level patent data. Patents and patent citations are the measurable outputs commonly arising from R&D activities (e.g., Pakes and Griliches 1984; Lev 1999). Since the early 1980s, changes in the legal environment and heightened technological competition have necessitated firms filing patents for many of their inventions to protect against potential infringement of their property rights.[13] Moreover, patents are realized inventions that are important to managers and investors, and are tradable assets with liquid markets (Lev 2001).

As a first step to constructing patent-based measures for capturing firm-level innovation performance, we retrieve the patent records of all U.S. public firms from a merged patent database that includes information on filing dates, patent assignees (i.e., companies), and COMPUSTAT-matched identifiers (GVKEY).[14] Also included are the citations made and

[12] Similarly, if the relevant benchmark is based on analyst forecast error (level of ROA), we exclude firm-years with negative analyst forecast error (negative ROA).

[13] In 1982, the Court of Appeals for the Federal Circuit (CAFC) was established for patent litigations due to some highly publicized patent infringement cases in the mid-1980s (e.g., the case of Texas Instruments against a number of Japanese semiconductor firms in 1985, and the case of Polaroid against Kodak in 1986). Since that time, U.S. firms have become more active in filing patents for their technological innovations (Hall and Ziedonis 2001; Hall 2004).

[14] We first combine the updated NBER patent data set developed by Hall et al. (2005b) and the patent data set of Kogan et al. (2017). The combined database includes detailed patent information for patents granted by the USPTO from 1976 to 2010. We then extend the database to all patents granted to 2014 by using the Google Patent database in Chen et al. (2016) and Gao et al. (2017). We employ an automated name-matching algorithm that matches the name and location of each patent assignee that appears in patents granted in 2011–2014 in the Google Patent database to a pool of names and locations that have appeared as assignees of patents listed in our merged database

received by each patent until the end of 2014, for all patents approved (granted) by the USPTO from 1976 to 2014. These firm-level patent data allow us to construct measures of firms' innovative activities along multiple dimensions and help us to capture the quantity and quality of these activities.

Our first measure, patent counts (*Counts*), is defined as the number of successful (i.e., approved) patent applications that are filed by focal firm *i* in sample year *t* (and are granted by the USPTO by 2014), divided by its book value of assets. This measure is also known as the number of patent grants by application years. This is a simple yet intuitive proxy, reflecting the quantity of the firm's innovation output (Scherer 1965; Griliches 1981). The second measure, patent citations (*Cites*), is defined as the total number of forward citations received by all successful patent applications filed by focal firm *i* in sample year *t*, divided by the book value of its assets.[15] The literature supports the notion that the number of patent citations reflects the economic value of a firm's inventions from the financial market's perspective (e.g., Trajtenberg 1990; Hall et al. 2005a). As an additional measure, we report our findings on the effects of R&D cuts on innovative efficiency (*Efficiency*), defined as the log-linearized number of patent counts divided by R&D expenditure (Lanjouw and Schankerman 2004; Cohen et al. 2013; Hirshleifer et al. 2013).

Three additional clarifications about our innovation measures follow. First, we construct all innovation-related variables (i.e., granted patents, forward citations of granted patents, and innovative efficiency) by *application* year in order to precisely capture firm-level innovation in

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from 1976 to 2010. As a result, we have the detailed information of U.S. public firms' patents granted from 1976 to 2014.

[15] Specifically, we use the adjusted number of citations; citations are subject to a vintage issue because it takes time for each patent to receive citations from subsequent patents. We use the adjustment factor developed by Hall et al. (2005b) and multiply the raw number of citations received by each patent with this factor to obtain adjusted patent citations.

each year, as firms have strong incentives to apply for patents soon after their inventions occur in order to protect their intellectual property (Hall et al. 2005b). This is appropriate because patent protection starts on the date of application. Second, we scale patent counts and citations by lagged total assets (in millions of dollars) of the focal firm to be consistent with equation (1) and the literature (e.g., Griliches 1981; Hall 1993; Eberhart et al. 2004; Hall et al. 2005a; Noel and Schankerman 2013). Third, our analyses focus on in-house R&D and internally generated patents, for a clean input-output relation to test our hypotheses.[16]

To capture firm-specific, time-varying innovation opportunities, we also construct a variable *BasicResearch* for firm *i* in year *t* that measures the intensity of innovative activities of U.S. universities in technology classes that firm *i* has also filed patents in over the past five years. For firm *i* in year *t*, we first calculate the ratios of technology classes in which it has filed patents from year $t-4$ to year *t*. Then, we calculate the total number of citations received by patents filed by U.S. universities in each technology class in year *t*. For firm *i* in year *t*, we calculate the weighted patent citations of U.S. universities based on the ratios of its technology classes as its *BasicResearch*. The idea of this variable is that, since firms' innovations are mainly applied science and follow basic science created by universities (Jaffe 1989; Trajtenberg et al. 1997), increases in universities' patenting activities in related technologies reflect improved innovative opportunities for firms.

Summary statistics

We present summary statistics in Table 1. We begin by presenting the average level of patent output, including both the number of patents (*Unscaled Counts*) and the number of

[16] See Sevilir and Tian (2012) and Bena and Li (2014) for discussions of acquiring innovation. Our results are robust to examining only firms with no goodwill (i.e., firms not engaging in acquisitions). In addition, see Yang et al. (2014) for discussions of using strategic alliances to acquire and generate innovation.

citations (*Unscaled Cites*) of sample firms, as well as the scaled innovation values used in our subsequent tables (*Counts*, *Cites*, and *Efficiency*). We then provide the sample characteristics for the following variables in panel A: the indicator variable for firms with a change in ROA greater than or equal to zero and less than 1 percent (*Benchmark*); the amount of REM-related R&D cuts from equation (3) (*R&DCut_REM*); the amount of all other R&D cuts from equation (3) (*R&DCut_Other*); R&D expense (*R&D*); book value of total assets (*Assets*); the market-to-book ratio (*MtoB*) defined as the value of the sample firm's market value of assets over its book value of assets; return on assets (*ROA*); the cash balance scaled by total assets (*Cash*); and the log of one plus the number of forward patent citations for university-filed patents that are in the same technology classes as the focal firm's patent portfolio (*BasicResearch*).[17] All variables are constructed with data from COMPUSTAT, except for the innovation-related measures. These variables are included in our regressions in order to control for the size, growth options, profitability, and cash levels that may be related to firms' innovation activities. The market-to-book ratio contains the market's assessment of firms' growth opportunities (Skinner and Sloan 2002; Roychowdhury 2006). It is worth noting that we also control for ROA and cash levels in our regressions in order to mitigate the potential issue that both abnormal R&D cuts and innovation are affected by an omitted variable related to financial strength.

Reported in panel A of Table 1 are the mean, median, and standard deviation of the innovation measures and other control variables used in our main sample (observations for which the one-year change in ROA is at least zero, that is, meeting or beating last year's ROA). In this panel, we have 36,042 firm-year observations and 8,166 distinct firms. Sample firms obtain a mean number of 19.6 patents per firm-year and are associated with 220.1 adjusted forward

[17] Regarding our variables from COMPUSTAT: the book value of assets is defined with AT; ROA is income before extraordinary items (IB) scaled by assets (AT); and cash balance is defined as (CHE) scaled by assets (AT).

citations. Firm-years meet or narrowly beat their earnings benchmark in 16 percent of observations. Their mean *R&DCut_REM* and *R&DCut_Other* are 0.2 percent and 5.5 percent of total assets, respectively. The median firm's book value of assets is $89 million, its market value is 1.8 times its book value, its ROA is 5.8 percent, and its cash position is 17 percent of total assets on average.

In panels B and C, we provide these sample statistics for the two samples that meet or beat our other two earnings benchmarks: analyst forecast error (panel B) and ROA (panel C). Consequently, in panels B and C, the benchmark indicator variables are denoted *Benchmark_FE* and *Benchmark_ROA*, respectively. Similarly, the measures for R&D cuts are also based on the different benchmarks, and thus we provide *R&DCut_REM_FE* and *R&DCut_Other_FE* in panel B, and *R&DCut_REM_ROA* and *R&DCut_Other_ROA* in panel C.

Although the sample characteristics are not dramatically different in these samples compared to the one used in panel A, one noteworthy difference is the significant decline in benchmark firms in panel C. Specifically, 6 percent of sample firm-years experience ROA between zero and 1 percent compared to 16 percent for the corresponding benchmark in panel A (ΔROA-based benchmark) and 26 percent for the corresponding benchmark in panel B (analyst forecast-based benchmark). The paucity of observations around that particular benchmark affects the average value of REM-related R&D cuts (*R&DCut_REM_ROA*) and affects some subsequent analyses, which we explain in more detail in our Table 3 discussion.[18]

Because innovation activities vary across industries, it is important for us to understand the distribution of our patent data by industry. Panel D presents the mean and standard deviation

[18] An alternative approach, to which our results are robust, is combining the benchmark based on ROA and one-year change in ROA, as in Gunny (2010). Regardless of the empirical approach, we recognize that some REM is not captured by our measure and also that not all R&D cuts are REM-related, even if we identify them as such.

for our main innovation measures in firm-year observations—patent counts, citations, and innovative efficiency—in 10 industries (these correspond to the Fama-French 12 industries, excluding financials and utilities): (1) consumer non-durables; (2) consumer durables; (3) manufacturing; (4) energy (oil, gas, and coal extraction and products); (5) chemicals (chemicals and allied products); (6) business equipment; (7) telephone and television transmission; (8) wholesale, retail, and some services; (9) healthcare (healthcare, medical equipment, and drugs); and (10) other. In panel D, we provide the results by industry for the sample that corresponds to panel A (change in ROA as benchmark). Panel D shows the high level of innovative output in many economic sectors and also the significant variation in innovative output by industry group. We find the highest level of patent counts and citations among consumer durables (mean values of 35.7 and 335.4 for patent counts and citations, respectively). Business equipment firms have the second-greatest number of patent counts (26.8 per firm-year) and patent citations (302.3). Innovative efficiency provides a different perspective on these results, given that certain industries tend to be relatively more patent-intensive relative to their R&D expenditures. In particular, we find the greatest innovative efficiency in consumer non-durables and telephone and television transmission industries—and the lowest in the R&D-intensive business equipment and healthcare industries. Given the variation in innovative output by sector, we control for industry affiliations of sample firms in our analyses.

4. Results

Baseline results

To test if REM affects innovation, we estimate the following ordinary least squares regressions for sample firm-year observations:[19]

$$Innovation_{i,t+h} = \beta_0 + \beta_1 R\&DCut\_REM_{i,t} + \beta_2 R\&DCut\_Other_{i,t} + \beta_3 Benchmark_{i,t} + \beta_4 R\&D_{i,t} + \beta_5 Assets_{i,t} + \beta_6 MtoB_{i,t} + \beta_7 Cash_{i,t} + \beta_8 ROA_{i,t} + \beta_9 InnovOpportunity_{i,t} + \beta_{10} Innovation_{i,t} + IndustryYear_{k(i),t} + \varepsilon_{i,t}, \quad (4a)$$

where $Innovation_{i,t+h}$ denotes $Counts_{i,t+h}$ or $Cites_{i,t+h}$ (patent counts and citations scaled by the book value of assets, respectively) of firm *i* in year *t*+*h*. We let *h* be one, two, and three to measure the middle- and long-term effect of R&D input on subsequent innovation in the following three years.[20] We also consider the sum of innovation during the following three years, $Innovation_{i,t+1,t+3}$.

For our tests with innovative efficiency, we modify equation (4a) to exclude R&D expenditure, given the mechanical effect of R&D on the *Efficiency* term (essentially, since efficiency reflects patent output per R&D expenditure, we avoid using R&D as an explanatory variable). Specifically, we model:

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[19] We recognize that REM-related R&D cuts could be endogenously determined by previous innovative performance (reverse causality) or by some unobservable, industry-specific factors that influence the occurrence of REM, R&D cuts, and innovation performance (i.e., omitted variables). To address such possibilities, we include lagged dependent variables and industry-year joint fixed effects in all of our regressions.

[20] We argue that it is reasonable to assume that the effect of REM (and the associated R&D cuts) on innovation manifests itself in three years. Hausman et al. (1984) and Hall et al. (1986) present evidence suggesting that the lag between R&D expenses and patent applications is actually quite short and could be less than one year.

$$Efficiency_{i,t+h} = \beta_0 + \beta_1 R\&DCut\_REM_{i,t} + \beta_2 R\&DCut\_Other_{i,t} + \beta_3 Benchmark_{i,t} + \beta_4 Assets_{i,t} + \beta_5 MtoB_{i,t} + \beta_6 Cash_{i,t} + \beta_7 ROA_{i,t} + \beta_8 InnovOpportunity_{i,t} + \beta_9 Efficiency_{i,t} + IndustryYear_{k(i),t} + \varepsilon_{i,t}, \quad (4b)$$

where the dependent variable $Efficiency_{i,t+h}$ is defined as the logarithm of firm *i*'s patent counts in year *t*+*h* divided by its R&D expenditure in year *t*−1.

As explained earlier, the total amount of abnormal R&D cuts associated with meeting an earnings benchmark is *R&DCut_REM*, whereas other abnormal R&D cuts are also included in the analysis as *R&DCut_Other*. We recognize that R&D cuts may be motivated by reasons other than REM, such as the cutting of R&D when there are weaker innovation opportunities. In our setting, the separation of these two types of cuts is intended to recognize whether a cut is more likely to be driven by the desire to meet an REM target, thus enabling us to focus on the incremental effect of REM-related cuts to R&D. All other control variables are as defined in section 3. $IndustryYear_{k(i),t}$ denotes the indicator variables for industry-year joint fixed effects for firm *i* in industry *k(i)*, defined by Fama-French 12 industry-group (excluding financials and utilities), in year *t*. Our statistical inferences are based on standard errors clustered at the firm level to correct for autocorrelation in regression errors.

We note that our full sample includes all COMPUSTAT firms with R&D expenditures over the 1987–2013 period (and we thus include granted patents that were initially filed from 1988 through 2014). Firm-years with zero patent output are included. For our main tests, we only include firms where the one-year change in ROA is greater than or equal to zero, as firms that miss earnings benchmarks would have different earnings management concerns.[21]

Table 2 presents the results of estimating equations (4a) and (4b). The benchmark we use in this table is meeting or narrowly beating a non-negative change in earnings (specifically, *Benchmark* equals one if the change in ROA is greater than or equal to zero and less than 1 percent, and is zero otherwise). The first four specifications examine a sample firm's number of patents ($Counts_{t+1}$, $Counts_{t+2}$, $Counts_{t+3}$, and $Counts_{t+1,t+3}$ as firm *i*'s patent counts in years *t*+1, *t*+2, *t*+3, and *t*+1 to *t*+3, respectively); the next four specifications examine the sample firm's patent citations ($Cites_{t+1}$, $Cites_{t+2}$, $Cites_{t+3}$, and $Cites_{t+1,t+3}$ as the sample firm's patent citations in years *t*+1, *t*+2, *t*+3, and *t*+1 to *t*+3, respectively); and the final four specifications examine the sample firm's innovative efficiency ($Efficiency_{t+1}$, $Efficiency_{t+2}$, $Efficiency_{t+3}$, and $Efficiency_{t+1,t+3}$ as the sample firm's innovative efficiency in years *t*+1, *t*+2, *t*+3, and *t*+1 to *t*+3, respectively).

We first note that REM is associated with significantly less patent output on average in the subsequent three years, as the associated coefficients of *R&DCut_REM* for $Counts_{t+1}$, $Counts_{t+2}$, $Counts_{t+3}$, and $Counts_{t+1,t+3}$ are −0.058, −0.089, −0.114, and −0.273, respectively. The latter three coefficients are significant at the 5 percent level or better. Those three coefficients suggest that a one standard deviation increase in *R&DCut_REM* is associated

[21] In later analyses, we obtain consistent results when we estimate equations (4a) and (4b) using all firm-year observations.

with a decline in patents of 3.0 percent, 3.9 percent, and 2.9 percent in years *t*+2, *t*+3, and *t*+1 to *t*+3, respectively.[22]

The value of *R&DCut_REM* also affects firms' future patent citations. In particular, the coefficients are −1.431, −2.039, −2.428, and −5.923 for $Cites_{t+1}$, $Cites_{t+2}$, $Cites_{t+3}$, and $Cites_{t+1,t+3}$, respectively. These coefficients indicate that a one standard deviation increase in *R&DCut_REM* is associated with statistically significant declines of 3.0 percent, 4.6 percent, 5.8 percent, and 3.9 percent in patent citations. Our regression analysis thus supports our hypothesis that REM has an adverse effect on firms' long-term innovation performance. For the regressions for *Counts* and *Cites*, we find that the loss in subsequent patents for other R&D cuts (*R&DCut_Other*) is negative and significant. The statistical significance is reasonable and is consistent with reduced innovation opportunities leading to R&D cuts, even when firms are not engaging in REM. A related interpretation of the coefficients *R&DCut_Other* and *R&DCut_REM* is that they represent the combined effect of reduced innovation opportunities and proximity to earnings targets. In particular, whereas a given reduction in innovation opportunities would generally coincide with both abnormal cuts to R&D (hence the significantly negative coefficient associated with *R&DCut_Other*), the coefficient of *R&DCut_REM* reflects the particularly extreme nature of R&D cuts when a firm is close to an earnings target.

The final four regressions provide evidence of the declines in innovative efficiency associated with REM-related R&D cuts. Specifically, the coefficients of *R&DCut_REM* are statistically significant at the 1 percent level, with values of −0.204, −0.251, −0.233, and −0.213 for $Efficiency_{t+1}$, $Efficiency_{t+2}$, $Efficiency_{t+3}$, and $Efficiency_{t+1,t+3}$, respectively. Those

[22] As an example, we calculate the coefficient estimated for $Counts_{t+2}$ (−0.089) multiplied by the standard deviation associated with *R&DCut_REM* (0.0052) and divide this product by the mean of *Counts* (0.0157), resulting in a 3.0 percent decline.

measures represent declines of 35.5 percent, 43.0 percent, 40.8 percent, and 36.0 percent, respectively. Moreover, other R&D cuts (*R&DCut_Other*) are statistically insignificant, thus not presenting evidence that non-REM related cuts to R&D are associated with reduced innovative efficiency. This finding supports our hypothesis from another perspective: since other R&D cuts are not driven by REM, they are less likely to incur certain REM-related frictions including contracting costs, division-level resistance to cuts, and managers' actions to obfuscate the extent of their earnings management. Thus, other R&D cuts are less harmful to firms' efficiency.

Of particular importance to our study is the different effect of REM-related R&D cuts compared to other R&D cuts. At the bottom of Table 2, we provide the *p*-value of the *F*-test for the difference in the two coefficients relating to R&D cuts, *R&DCut_REM* and *R&DCut_Other*. Specifically, we find that in all but two specifications (those of $Counts_{t+1}$ and $Cites_{t+1}$), REM-related R&D cuts are associated with significantly larger declines in innovative performance compared to other cuts to R&D.

The coefficient estimates for the control variables are largely consistent with economic intuition and with the prior literature. We find that subsequent patents are positively associated with $R\&D_{i,t}$ (as expected, its coefficient is significantly positive, consistent with higher R&D expenditure leading to more subsequent innovations). We also find that subsequent patents are positively associated with $MtoB_{i,t}$, $Cash_{i,t}$, $ROA_{i,t}$, $BasicResearch_{i,t}$, and $Innovation_{i,t}$, suggesting that firms with higher R&D levels, more growth opportunities, more cash, better profitability, more opportunities to innovate, and more prior patents (or citations) tend to produce more patents in the future.[23]

[23] We use the logarithmic value of one plus $R\&D_{i,t}$, $Assets_{i,t}$, and $BasicResearch_{i,t}$ in our regressions; the interpretation of the coefficient of $R\&D_{i,t}$ would thus differ from that of $R\&DCut\_REM_{i,t}$ or $R\&DCut\_Other_{i,t}$ in

Alternative benchmarks

While our main analyses focus on the change in ROA around zero as the reported earnings benchmark, in Table 3 we present the results using two alternative benchmarks.

In panel A of Table 3, we use meeting analyst forecasts as an alternative benchmark for REM-related R&D cuts. Using this alternative approach, the coefficients of our measure for REM-related R&D cuts, *R&DCut_REM_FE*, remains negative and significant, as do the coefficients of our measure for other R&D cuts (*R&DCut_Other_FE*). Moreover, *R&DCut_REM_FE* remains significantly different from *R&DCut_Other_FE*, consistent with the particularly harmful effects of R&D cuts driven by earnings management concerns. Regarding the economic significance of the three-year cumulative measures, we find that the three-year cumulative values $Counts_{t+1,t+3}$ declines by 5.0 percent, $Cites_{t+1,t+3}$ declines by 4.7 percent, and $Efficiency_{t+1,t+3}$ declines by 29.0 percent, following a one standard deviation increase in *R&DCut_REM_FE*. Corresponding to our results in Table 2, the coefficient of *R&DCut_REM_FE* is significantly lower than that of *R&DCut_Other_FE,* reflecting the more severe effect of REM-related cuts on patent output.

As another alternative benchmark, in panel B we consider meeting or narrowly beating zero ROA as the benchmark of interest. Compared to our previous tables, the number of observations where firms had met or narrowly beaten this benchmark is significantly smaller,

magnitude. The negative coefficient associated with $Assets_{i,t}$ is mechanical, as we scale *Counts* and *Cites* by the book value of assets.

thus contributing to reduced statistical power.[24] The effect of this reduced power manifests itself in the *Counts* regressions, where our REM-related measure is statistically insignificant. In the subsequent regressions for *Cites* and *Efficiency*, we find greater statistical significance associated with *R&DCut_REM_ROA*. Specifically, a one standard deviation increase in *R&DCut_REM* is associated with declines of 3.1 percent and 19.5 percent in three-year cumulative $Cites_{t+1,t+3}$ and $Efficiency_{t+1,t+3}$, respectively. Moreover, we note that for those regressions (and corresponding to the previous results), the coefficient of *R&DCut_REM_ROA* generally remains significantly lower than that of *R&DCut_Other_ROA*.

We also observe that the coefficients of *R&DCut_REM_FE* and *R&DCut_REM_ROA* are commensurate with the coefficients of *R&DCut_REM* reported in Table 2. This is important because it suggests that the magnitude of the impact of REM-related cuts to R&D is not sensitive to our benchmark choice. This finding also suggests that the less significant coefficients in panel B of Table 3 are likely driven by statistical power.

Matching analyses

To address the alternative explanation that our results are driven by firms' innovation opportunities, we next conduct our analyses with a matched sample. We use coarsened exact matching as introduced in Blackwell et al. (2009) and Iacus et al. (2011). This technique effectively mitigates the imbalance in the characteristics of treated firms and control firms.[25]

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[24] As we note in our discussion of Table 1 panel C, there are only 2,509 observations in this sample with ROA greater than or equal to zero and less than 1 percent; firm-year observations are simply less likely to occur around this benchmark, in contrast to analyst forecast error.

[25] This method has been used in Feldman et al. (2014), DeFond et al. (2016), Balsmeier et al. (2017), and Bereskin et al. (2017).

With coarsened exact matching, each firm with *R&DCut_REM* greater than zero is matched with corresponding observations in the same year on the following proxies for innovation opportunities: size (the log of one plus the book value of assets), market-to-book (the market value of assets divided by the book value of assets), R&D (the natural log of one plus R&D expenditure), and basic research (the natural log of one plus the number of patent citations of university-filed patents that are in the same technology classes as the focal firm's patent portfolio).

In Table 4, we provide the results from our sample formed through coarsened exact matching analysis. Our results remain comparable to those in Table 2. In particular, the coefficient associated with *R&DCut_REM* remains consistently negative and significant, and significantly different from the coefficient associated with *R&DCut_Other*. Findings for the other explanatory variables also remain generally comparable to those reported in Table 2.

We also observe that the statistical and economic significance of *R&DCut_REM* is consistently larger in Table 4 compared to the corresponding value in Table 2. For example, considering the change in the three-year cumulative values for $Counts_{t+1,t+3}$, $Cites_{t+1,t+3}$, and $Efficiency_{t+1,t+3}$, a one standard deviation increase in *R&DCut_REM* is associated with declines of 4.9 percent, 6.4 percent, and 49.9 percent, respectively. This finding suggests that when we better control for firm-specific innovation opportunities, the estimated impact of REM-related R&D cuts on subsequent innovation is even greater, which corroborates our results.

Additional earnings characteristics

In our main analyses we restrict our observations to firm-years with a one-year change in ROA greater than or equal to zero. In Table 5, we report additional findings where we broaden our sample to include firm-years that do not meet this constraint (i.e., we include observations where change in ROA is negative). In this table, we show that the coefficients on *R&DCut_REM* and *R&DCut_Other* remain negative and significant in this broader sample.

Using this broader sample that includes firm-years with weaker performance, we also add the variables $Beat_{i,t}$ and $JustMiss_{i,t}$, corresponding to Gunny's (2010) approach to address the nature of firms' earnings. $Beat_{i,t}$ is an indicator variable set to one if firm *i*'s change in ROA is greater than or equal to 1 percent in year *t*, and zero otherwise, and $JustMiss_{i,t}$ is an indicator variable set to one if firm *i*'s change in ROA is lower than zero but greater than or equal to −1 percent in year *t*, and zero otherwise. The coexistence of $Benchmark_{i,t}$, $Beat_{i,t}$, and $JustMiss_{i,t}$ helps us to more closely examine whether our specifications are truly capturing REM as opposed to other earnings characteristics. Once again, we note that our results remain similar in economic and statistical significance compared to those reported when using our previous specifications.

Reversals of cuts

We next attempt to improve the identification of REM-related R&D cuts. We examine whether *R&DCut_REM* is associated with a subsequent reversal, as this would provide additional evidence that the cut was indeed REM-related. The intuition is that when managers increase R&D investment shortly after committing to deep R&D cuts, they may be attempting to "catch up" in innovation in order to recover the loss and delay due to REM. In Table 6, we define an indicator variable *RevertIndicator* that is set equal to one if a firm's three-year growth in R&D intensity from year *t* to *t*+3 is higher than that of the sample mean, and to zero otherwise.

We note that the interaction term *RevertIndicator*×*R&DCut_REM* is generally negative and significant for regressions for *Counts* and *Cites*. This provides further evidence of the detrimental effects of REM-related R&D cuts. For the regressions with patent efficiency, *R&DCut_REM* remains negative and significant, whereas the interaction term *RevertIndicator*×*R&DCut_REM* is insignificant. The insignificant coefficient of *RevertIndicator*×*R&DCut_REM* in the *Efficiency* regressions could be attributed to confounding effects from fluctuations in R&D leading to reduced efficiency in general.

5. Conclusions

In the earnings management literature, little evidence has so far been presented on the consequences associated with the management of firms' real activities. One of the major reasons for this is the difficulty in defining a measure of a firm's "output" that is closely related to a real activity's "input" that was managed. The close relation between R&D expenditures and patent output enables us to use patent data to address this gap in the literature. Moreover, as the patent data are rich and include measures for both the quantity and quality of innovative output, they allow us to describe the impact of REM on firms' innovations along multiple dimensions and over time.

We design an approach to measure the decline in innovation associated with both REM-related R&D cuts and other R&D cuts. We find that REM-related cuts significantly reduce firms' patent output and have significantly greater effects than other cuts to R&D. The effect of an REM-related decline in R&D spending on innovation is economically substantial and statistically significant.

We also find that REM-related R&D cuts lead to lower innovative efficiency than do other R&D cuts. This finding supports our arguments on the suboptimal nature of management decisions motivated by earnings management concerns. Further analyses suggest that the adverse effect of REM on innovation is less likely to be attributed to omitted variables such as innovation opportunities; instead, it appears more likely to be driven primarily by the complications associated with engaging in REM.

Our study contributes to the literature by presenting new evidence on the extent to which REM affects firms from an innovation perspective and suggests that manipulation of R&D expenditures may severely affect firms' technological competencies and long-term prospects.

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TABLE 1
Sample statistics

Panel A: ΔROA as benchmark

	Mean	Median	Std. dev.
Unscaled Counts	19.6	0.0	145.0
Unscaled Cites	220.1	0.0	1,864.0
Counts	0.02	0.00	0.04
Cites	0.25	0.00	0.80
Efficiency	0.003	0.000	0.05
Benchmark	0.16	0.00	0.36
R&DCut_REM	0.002	0.00	0.01
R&DCut_Other	0.055	0.00	0.14
R&D ($ million)	46.0	4.9	115.2
Assets ($ million)	2,487.5	88.9	9,191.3
MtoB	3.5	1.8	6.0
ROA	-0.05	0.06	0.30
Cash	0.26	0.17	0.25
BasicResearch	2.4	0.0	2.9
Observations	36,042		

Panel B: Analyst forecast as benchmark

	Mean	Median	Std. dev.
Unscaled Counts	31.7	1.0	189.5
Unscaled Cites	284.1	1.0	1,888.1
Counts	0.02	0.00	0.04
Cites	0.25	0.00	0.78
Efficiency	0.003	0.000	0.06
Benchmark_FE	0.26	0.00	0.44
R&DCut_REM_FE	0.002	0.00	0.00
R&DCut_Other_FE	0.029	0.00	0.06
R&D ($ million)	76.9	19.6	140.4
Assets ($ million)	3,738.5	320.8	11,356.2
MtoB	2.5	1.8	2.5
ROA	0.02	0.07	0.22
Cash	0.29	0.22	0.25
BasicResearch	3.0	3.2	2.9
Observations	18,619		

Panel C: ROA as benchmark

	Mean	Median	Std. dev.
Unscaled Counts	28.3	0.0	169.9
Unscaled Cites	322.3	0.0	2,210.8
Counts	0.01	0.00	0.03
Cites	0.23	0.00	0.73
Efficiency	0.004	0.000	0.06
Benchmark_ROA	0.06	0.00	0.25
R&DCut_REM_ROA	0.000	0.00	0.00
R&DCut_Other_ROA	0.048	0.00	0.13
R&D ($ million)	66.6	8.7	139.5
Assets ($ million)	4,014.3	255.6	11,729.0
MtoB	2.2	1.6	2.4
ROA	0.11	0.10	0.10
Cash	0.20	0.13	0.20
BasicResearch	2.6	1.1	2.8
Observations	38,706		

Panel D: Innovation by industry

		Patents		Patent citations		Efficiency	
	N	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Consumer Non-Durables	1,271	3.8	16.5	37.6	146.4	0.018	0.132
Consumer Durables	1,556	35.7	181.2	335.4	1,655.1	0.010	0.102
Manufacturing	6,438	22.5	151.7	225.5	1,477.4	0.008	0.087
Oil, Gas, and Coal Extraction and Products	687	21.7	59.0	56.8	831.7	0.014	0.115
Chemicals and Allied Products	1,554	22.1	66.9	222.7	903.1	0.006	0.075
Business Equipment	13,838	26.8	193.9	302.3	2,673.9	0.002	0.043
Telephone and Television Transmission	674	11.3	52.6	184.3	1,322.5	0.018	0.138
Wholesale, Retail, and Some Services	735	2.1	12.5	17.2	74.7	0.006	0.072
Healthcare, Medical Equipment, and Drugs	7,270	6.8	27.4	124.5	711.6	0.002	0.046
Other	2,019	10.2	95.2	81.7	724.8	0.004	0.064

This table reports summary statistics for the variables used in our paper, using COMPUSTAT data from 1987 through 2013. Our variables are *Unscaled Counts* (patent grants), *Unscaled Cites* (the number of forward patent citations received by those patents), *Counts* (patent grants scaled by assets in millions of dollars), *Cites* (the number of forward patent citations received by those patents, scaled by assets in millions of dollars), *Efficiency* (defined as the natural log of [1 + *Unscaled Counts* / (1 + *R&D expenditure*)]), *Benchmark* (an indicator variable equal to one if the one-year change in ROA (income before extraordinary items scaled by assets) is greater than or equal to zero and less than 1 percent, and zero otherwise), *R&DCut_REM* and *R&DCut_Other* (as specified in equation (3), where the benchmark from equation (3) is based on the one-year change in ROA being equal to zero), *R&D* (R&D expense, in millions), *Assets* (the book value of assets), *MtoB* (the market value of assets divided by the book value of assets), *ROA* (income before extraordinary items scaled by assets), *Cash* (cash balance scaled by assets), *BasicResearch* (the natural log of one plus the number of forward patent citations for university-filed patents that are in the same technology class as the focal firm's patent portfolio), *Benchmark_FE* (an indicator variable equal to one for firm-years where the analyst forecast error is greater than or equal to zero and less than 0.01 per share), *R&DCut_REM_FE* and *R&DCut_Other_FE* (as specified in equation (3), where the benchmark from equation (3) is based on the analyst forecast error being equal to zero), *Benchmark_ROA* (an indicator variable equal to one for firm-years where the ROA is greater than or equal to zero and less than 1 percent), *R&DCut_REM_ROA* and *R&DCut_Other_ROA* (as specified in equation (3), where the benchmark from equation (3) is based on the ROA being equal to zero). Panel A provides the summary statistics for the sample with one-year change in ROA greater than or equal to zero; panel B provides the summary statistics for the sample with analyst forecast error greater than or equal to zero; panel C provides the summary statistics for the sample with ROA greater than or equal to zero; and panel D provides the distribution by Fama-French 12 industry-group (excluding financials and utilities) for the sample used where the one-year change in ROA is greater than or equal to zero. Throughout the paper, patent data are based on the application year of the patent, conditional on the patent being subsequently approved.

TABLE 2

Effects of abnormal R&D cuts on innovation

	$Counts_{t+1}$	$Counts_{t+2}$	$Counts_{t+3}$	$Counts_{t+1,t+3}$	$Cites_{t+1}$	$Cites_{t+2}$	$Cites_{t+3}$	$Cites_{t+1,t+3}$	$Efficiency_{t+1}$	$Efficiency_{t+2}$	$Efficiency_{t+3}$	$Efficiency_{t+1,t+3}$
R&DCut_REM	**-0.058**	**-0.089****	**-0.114*****	**-0.273****	**-1.431***	**-2.039****	**-2.428*****	**-5.923****	**-0.204*****	**-0.251*****	**-0.233*****	**-0.213*****
	(0.036)	(0.038)	(0.044)	(0.110)	(0.849)	(0.841)	(0.896)	(2.715)	(0.074)	(0.074)	(0.082)	(0.069)
R&DCut_Other	-0.008***	-0.007***	-0.006***	-0.021***	-0.120***	-0.104***	-0.081***	-0.309***	0.000	0.001	-0.000	-0.000
	(0.001)	(0.002)	(0.002)	(0.004)	(0.026)	(0.024)	(0.023)	(0.079)	(0.002)	(0.002)	(0.002)	(0.002)
Benchmark	-0.001**	-0.001*	-0.000	-0.003*	-0.019	-0.015	0.009	-0.047	0.002	0.002	0.003*	0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.013)	(0.012)	(0.013)	(0.038)	(0.001)	(0.001)	(0.002)	(0.001)
R&D	0.000***	0.000***	0.000***	0.001***	0.008***	0.009***	0.008***	0.029***				
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.003)				
Assets	-0.002***	-0.001***	-0.001***	-0.005***	-0.033***	-0.026***	-0.024***	-0.109***	-0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.003)	(0.003)	(0.011)	(0.000)	(0.000)	(0.000)	(0.000)
MtoB	0.000	0.000**	0.000***	0.001***	0.004***	0.005***	0.005***	0.017***	0.000	0.000*	0.000*	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)
Cash	0.011***	0.013***	0.013***	0.038***	0.175***	0.183***	0.183***	0.640***	-0.000	0.001	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.004)	(0.024)	(0.024)	(0.024)	(0.084)	(0.001)	(0.001)	(0.001)	(0.001)
ROA	0.004***	0.005***	0.007***	0.013***	0.086***	0.098***	0.114***	0.258***	0.002**	0.002**	0.002*	0.002***
	(0.001)	(0.001)	(0.001)	(0.004)	(0.023)	(0.022)	(0.022)	(0.082)	(0.001)	(0.001)	(0.001)	(0.001)
BasicResearch	0.004***	0.004***	0.003***	0.011***	0.081***	0.067***	0.059***	0.223***	0.000	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.003)	(0.003)	(0.011)	(0.000)	(0.000)	(0.000)	(0.000)
$Counts_t$	0.173***	0.144***	0.129***	0.468***								
	(0.014)	(0.013)	(0.011)	(0.036)								
$Cites_t$					0.030***	0.026***	0.022***	0.090***				
					(0.008)	(0.007)	(0.006)	(0.025)				
$Efficiency_t$									0.178***	0.167***	0.151***	0.158***
									(0.020)	(0.020)	(0.020)	(0.018)
Constant	0.023***	0.018***	0.018***	0.068***	0.472***	0.350***	0.329***	1.583***	0.002	0.001	0.000	0.002
	(0.003)	(0.003)	(0.003)	(0.008)	(0.053)	(0.051)	(0.050)	(0.181)	(0.002)	(0.002)	(0.003)	(0.002)
Observations	36,042	34,865	33,857	33,857	36,042	34,865	33,857	33,857	36,042	34,865	33,857	33,857
R^2	32.28%	27.95%	25.43%	33.50%	24.58%	23.08%	21.66%	26.53%	16.84%	14.93%	12.91%	17.20%
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
***p*(*R&DCut_REM* = *R&DCut_Other*)**	**0.1572**	**0.0300**	**0.0128**	**0.0218**	**0.1219**	**0.0211**	**0.0087**	**0.0383**	**0.0056**	**0.0006**	**0.0047**	**0.0021**

This table reports the effects of REM on innovation. Our dependent variables are *Counts*, *Cites*, and *Efficiency* examined in the following one year (t+1), two years (t+2), three years (t+3), and cumulative three years (t+1 through t+3). See the notes to Table 1 for variable definitions. The time placer t is from 1987 to 2013, and we thus include patent data until 2014. We exclude financial and utility firms, firms with zero R&D expense, and firms with negative one-year change in ROA. Industry-year fixed effects are included (at the year and Fama-French 12 industry levels). Robust firm-clustered standard errors are provided in parentheses below the coefficient value. *, **, and *** denote significant differences from zero at the 10 percent, 5 percent, and 1 percent levels, respectively.

TABLE 3

Panel A: Benchmark defined with analyst forecast error

	$Counts_{t+1}$	$Counts_{t+2}$	$Counts_{t+3}$	$Counts_{t+1,t+3}$	$Cites_{t+1}$	$Cites_{t+2}$	$Cites_{t+3}$	$Cites_{t+1,t+3}$	$Efficiency_{t+1}$	$Efficiency_{t+2}$	$Efficiency_{t+3}$	$Efficiency_{t+1,t+3}$
R&DCut_REM_FE	**-0.137****	**-0.185*****	**-0.193*****	**-0.533*****	**-2.937****	**-2.902****	**-1.934**	**-7.472***	**-0.241****	**-0.193***	**-0.184***	**-0.199****
	(0.061)	(0.064)	(0.067)	(0.186)	(1.316)	(1.215)	(1.184)	(3.978)	(0.096)	(0.105)	(0.105)	(0.093)
R&DCut_Other_FE	-0.014***	-0.007	-0.009*	-0.027**	-0.304***	-0.137*	-0.120	-0.530**	-0.010**	-0.012**	-0.007	-0.010**
	(0.004)	(0.005)	(0.005)	(0.014)	(0.074)	(0.081)	(0.073)	(0.242)	(0.005)	(0.006)	(0.006)	(0.005)
Benchmark_FE	-0.001	0.000	0.000	0.001	0.004	0.011	0.002	0.035	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.016)	(0.015)	(0.015)	(0.050)	(0.001)	(0.001)	(0.001)	(0.001)
R&D	0.001***	0.001***	0.001***	0.002***	0.005**	0.006***	0.005**	0.014**				
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.002)	(0.007)				
Assets	-0.002***	-0.002***	-0.001***	-0.005***	-0.029***	-0.026***	-0.021***	-0.091***	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.005)	(0.005)	(0.004)	(0.015)	(0.000)	(0.000)	(0.000)	(0.000)
MtoB	0.001***	0.001***	0.001***	0.004***	0.027***	0.025***	0.024***	0.092***	0.000	0.000*	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.001)	(0.004)	(0.004)	(0.004)	(0.014)	(0.000)	(0.000)	(0.000)	(0.000)
Cash	0.008***	0.009***	0.010***	0.028***	0.114***	0.131***	0.135***	0.416***	-0.002*	-0.002	0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.006)	(0.036)	(0.036)	(0.037)	(0.117)	(0.001)	(0.002)	(0.002)	(0.001)
ROA	0.001	0.003	0.007***	0.010	0.013	0.049	0.068	0.005	0.002	0.003*	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.007)	(0.044)	(0.042)	(0.042)	(0.152)	(0.002)	(0.001)	(0.001)	(0.001)
BasicResearch	0.003***	0.003***	0.003***	0.009***	0.067***	0.059***	0.046***	0.182***	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.004)	(0.004)	(0.004)	(0.013)	(0.000)	(0.000)	(0.000)	(0.000)
$Counts_t$	0.289***	0.249***	0.215***	0.734***								
	(0.033)	(0.029)	(0.024)	(0.085)								
$Cites_t$					0.077***	0.066***	0.051***	0.203***				
					(0.020)	(0.017)	(0.012)	(0.052)				
$Efficiency_t$									0.182***	0.170***	0.155***	0.156***
									(0.022)	(0.022)	(0.021)	(0.019)
Constant	0.022***	0.021***	0.016***	0.061***	0.426***	0.346***	0.256***	1.300***	0.006	0.003	-0.004	0.001
	(0.004)	(0.004)	(0.005)	(0.014)	(0.088)	(0.089)	(0.083)	(0.295)	(0.004)	(0.005)	(0.005)	(0.004)
Observations	18,619	17,746	16,889	16,889	18,619	17,746	16,889	16,889	18,619	17,746	16,889	16,889
R^2	47.09%	40.82%	34.04%	43.59%	34.94%	32.84%	28.30%	34.32%	24.68%	21.44%	21.68%	25.29%
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
p(R&DCut_REM_FE = R&DCut_Other_FE)	**0.0417**	**0.0049**	**0.0052**	**0.0058**	**0.0435**	**0.0218**	**0.1230**	**0.0788**	**0.0152**	**0.0824**	**0.0906**	**0.0413**

Panel B: Benchmark defined with ROA

	$Counts_{t+1}$	$Counts_{t+2}$	$Counts_{t+3}$	$Counts_{t+1,t+3}$	$Cites_{t+1}$	$Cites_{t+2}$	$Cites_{t+3}$	$Cites_{t+1,t+3}$	$Efficiency_{t+1}$	$Efficiency_{t+2}$	$Efficiency_{t+3}$	$Efficiency_{t+1,t+3}$
R&DCut_REM_ROA	**-0.091**	**-0.080**	**-0.199**	**-0.452**	**-5.392***	**-4.106**	**-5.458****	**-15.176***	**-0.341**	**-0.451***	**-0.499***	**-0.484****
	(0.121)	(0.122)	(0.131)	(0.331)	(2.838)	(2.612)	(2.758)	(8.186)	(0.230)	(0.246)	(0.270)	(0.228)
R&DCut_Other_ROA	-0.007***	-0.008***	-0.009***	-0.024***	-0.133***	-0.134***	-0.121***	-0.406***	-0.003	-0.005*	-0.005*	-0.004**
	(0.001)	(0.001)	(0.002)	(0.004)	(0.022)	(0.020)	(0.020)	(0.067)	(0.002)	(0.003)	(0.002)	(0.002)
Benchmark_ROA	-0.001	-0.001	-0.000	-0.002	0.028	0.002	0.013	0.052	0.002	0.002	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.018)	(0.018)	(0.019)	(0.058)	(0.002)	(0.002)	(0.002)	(0.002)
R&D	0.000***	0.000***	0.000***	0.001***	0.008***	0.008***	0.006***	0.023***				
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.003)				
Assets	-0.001***	-0.001***	-0.001***	-0.004***	-0.027***	-0.023***	-0.020***	-0.094***	-0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.003)	(0.003)	(0.011)	(0.000)	(0.000)	(0.000)	(0.000)
MtoB	0.000***	0.001***	0.001***	0.002***	0.012***	0.012***	0.012***	0.044***	0.000	0.000*	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.003)	(0.008)	(0.000)	(0.000)	(0.000)	(0.000)
Cash	0.006***	0.008***	0.010***	0.026***	0.153***	0.178***	0.188***	0.591***	-0.001	0.000	0.000	-0.000
	(0.001)	(0.001)	(0.002)	(0.004)	(0.032)	(0.033)	(0.033)	(0.114)	(0.001)	(0.001)	(0.001)	(0.001)
ROA	0.006***	0.009***	0.012***	0.029***	0.183***	0.232***	0.275***	0.785***	0.004**	0.002	0.002	0.003
	(0.002)	(0.002)	(0.002)	(0.007)	(0.045)	(0.048)	(0.052)	(0.169)	(0.002)	(0.002)	(0.002)	(0.002)
BasicResearch	0.003***	0.003***	0.003***	0.008***	0.063***	0.056***	0.052***	0.181***	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.003)	(0.003)	(0.010)	(0.000)	(0.000)	(0.000)	(0.000)
$Counts_t$	0.322***	0.293***	0.255***	0.879***								
	(0.027)	(0.025)	(0.024)	(0.075)								
$Cites_t$					0.116***	0.099***	0.083***	0.317***				
					(0.016)	(0.015)	(0.013)	(0.048)				
$Efficiency_t$									0.177***	0.164***	0.153***	0.152***
									(0.015)	(0.014)	(0.014)	(0.013)
Constant	0.018***	0.015***	0.013***	0.052***	0.368***	0.278***	0.245***	1.307***	0.002	0.001	-0.000	0.001
	(0.002)	(0.003)	(0.003)	(0.009)	(0.055)	(0.056)	(0.057)	(0.197)	(0.002)	(0.002)	(0.003)	(0.002)
Observations	38,706	37,461	36,189	36,189	38,706	37,461	36,189	36,189	38,706	37,461	36,189	36,189
R^2	38.02%	33.97%	28.89%	38.35%	31.24%	28.58%	25.75%	31.50%	21.57%	18.31%	16.44%	20.52%
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
***p*(*R&DCut_REM_ROA* = *R&DCut_Other_ROA*)**	**0.4860**	**0.5533**	**0.1466**	**0.1958**	**0.0636**	**0.1278**	**0.0528**	**0.0708**	**0.1415**	**0.0699**	**0.0671**	**0.0352**

This table reports the effects of REM on innovation, using alternative earnings benchmarks to identify the role of earnings management. Our dependent variables are *Counts*, *Cites*, and *Efficiency* examined in the following one year (*t*+1), two years (*t*+2), three years (*t*+3), and cumulative three years (*t*+1 through *t*+3). See the notes to Table 1 for variable definitions. The time placer *t* is from 1987 to 2013, and we thus include patent data until 2014. We exclude financial and utility firms, firms with zero R&D expense, and firms with either negative analyst forecast error (panel A) or negative ROA (panel B). Industry-year fixed effects are included (at the year and Fama-French 12 industry levels). Robust firm-clustered standard errors are provided in parentheses below the coefficient value. *, **, and *** denote significant differences from zero at the 10 percent, 5 percent, and 1 percent levels, respectively.

TABLE 4
Matching analysis

	$Counts_{t+1}$	$Counts_{t+2}$	$Counts_{t+3}$	$Counts_{t+1,t+3}$	$Cites_{t+1}$	$Cites_{t+2}$	$Cites_{t+3}$	$Cites_{t+1,t+3}$	$Efficiency_{t+1}$	$Efficiency_{t+2}$	$Efficiency_{t+3}$	$Efficiency_{t+1,t+3}$
R&DCut_REM	**-0.101***	**-0.162*****	**-0.209*****	**-0.521*****	**-3.260****	**-3.730*****	**-4.729*****	**-12.016*****	**-0.286****	**-0.290****	**-0.372*****	**-0.324****
	(0.054)	(0.062)	(0.069)	(0.181)	(1.487)	(1.432)	(1.478)	(4.559)	(0.115)	(0.119)	(0.140)	(0.127)
R&DCut_Other	-0.012***	-0.013***	-0.012***	-0.036***	-0.156***	-0.192***	-0.165***	-0.485***	0.003	0.003	0.001	0.003
	(0.002)	(0.002)	(0.003)	(0.007)	(0.037)	(0.031)	(0.032)	(0.110)	(0.002)	(0.002)	(0.002)	(0.002)
Benchmark	-0.000	0.001	0.002	0.002	0.016	0.021	0.050*	0.081	0.004*	0.003	0.005*	0.004*
	(0.001)	(0.001)	(0.001)	(0.003)	(0.026)	(0.025)	(0.026)	(0.080)	(0.002)	(0.002)	(0.003)	(0.002)
R&D	0.000***	0.001***	0.001***	0.002***	0.010**	0.014***	0.015***	0.044***				
	(0.000)	(0.000)	(0.000)	(0.001)	(0.004)	(0.002)	(0.002)	(0.009)				
Assets	-0.001***	-0.001***	-0.002***	-0.004***	-0.039***	-0.033***	-0.034***	-0.141***	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.007)	(0.005)	(0.005)	(0.019)	(0.000)	(0.000)	(0.000)	(0.000)
MtoB	0.000***	0.000***	0.001***	0.001***	0.008***	0.008***	0.010***	0.030***	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.002)	(0.006)	(0.000)	(0.000)	(0.000)	(0.000)
Cash	0.012***	0.016***	0.016***	0.046***	0.228***	0.267***	0.264***	0.878***	0.001	-0.001	-0.001	-0.000
	(0.002)	(0.002)	(0.002)	(0.006)	(0.043)	(0.041)	(0.042)	(0.139)	(0.002)	(0.002)	(0.002)	(0.002)
ROA	0.007***	0.011***	0.013***	0.026***	0.112**	0.172***	0.221***	0.524***	0.000	0.000	-0.001	0.000
	(0.002)	(0.002)	(0.002)	(0.006)	(0.047)	(0.037)	(0.039)	(0.137)	(0.002)	(0.002)	(0.002)	(0.002)
BasicResearch	0.003***	0.003***	0.003***	0.009***	0.086***	0.070***	0.065***	0.237***	0.000	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.005)	(0.004)	(0.004)	(0.014)	(0.000)	(0.000)	(0.000)	(0.000)
$Counts_t$	0.250***	0.202***	0.167***	0.631***								
	(0.018)	(0.018)	(0.017)	(0.051)								
$Cites_t$					0.034**	0.029**	0.025***	0.097**				
					(0.014)	(0.012)	(0.009)	(0.041)				
$Efficiency_t$									0.211***	0.207***	0.189***	0.202***
									(0.039)	(0.039)	(0.038)	(0.037)
Constant	0.019***	0.017***	0.019***	0.060***	0.550***	0.373***	0.392***	1.903***	-0.005	-0.002	-0.006	-0.004
	(0.004)	(0.004)	(0.005)	(0.012)	(0.103)	(0.095)	(0.099)	(0.330)	(0.007)	(0.007)	(0.007)	(0.007)
Observations	30,984	29,851	28,873	28,873	30,984	29,851	28,873	28,873	30,984	29,851	28,873	28,873
R^2	38.22%	31.19%	26.45%	35.84%	25.98%	24.97%	24.16%	27.82%	19.20%	18.71%	16.51%	19.94%
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
p(R&DCut_REM = R&DCut_Other)	**0.0932**	**0.0158**	**0.0038**	**0.0072**	**0.0363**	**0.0134**	**0.0020**	**0.0113**	**0.0125**	**0.0143**	**0.0079**	**0.0101**

The regressions in this table follow from Table 2, using a sample from coarsened exact matching. In coarsened exact matching, each treatment firm (defined as an observation where *R&DCut_REM* is greater than zero) is matched with corresponding observations in the same year on the following proxies for investment opportunities: size (the log of one plus the book value of assets), market-to-book (the market value of assets divided by the book value of assets), R&D (the natural log of one plus R&D expenditure), and basic research (the natural log of one plus the number of forward patent citations for university-filed patents that are in the same technology class as the focal firm's patent portfolio). Our dependent variables are *Counts*, *Cites*, and *Efficiency* examined in the following one year (*t*+1), two years (*t*+2), three years (*t*+3), and cumulative three years (*t*+1 through *t*+3). See the notes to Table 1 for variable definitions. The time placer *t* is from 1987 to 2013, and we thus include patent data until 2014. We exclude financial and utility firms, firms with zero R&D expense, and firms with negative one-year change in ROA. Industry-year fixed effects are included (at the year and Fama-French 12 industry levels). Robust firm-clustered standard errors are provided in parentheses below the coefficient value. *, **, and *** denote significant differences from zero at the 10 percent, 5 percent, and 1 percent levels, respectively.

TABLE 5
Including firm-years with all performance levels, and additional controls for earnings performance

	$Counts_{t+1}$	$Counts_{t+2}$	$Counts_{t+3}$	$Counts_{t+1,t+3}$	$Cites_{t+1}$	$Cites_{t+2}$	$Cites_{t+3}$	$Cites_{t+1,t+3}$	$Efficiency_{t+1}$	$Efficiency_{t+2}$	$Efficiency_{t+3}$	$Efficiency_{t+1,t+3}$
R&DCut_REM	**-0.060**	**-0.083****	**-0.108****	**-0.261****	**-1.517***	**-2.044****	**-2.366*****	**-6.005****	**-0.225*****	**-0.242*****	**-0.245*****	**-0.223*****
	(0.037)	(0.038)	(0.044)	(0.114)	(0.844)	(0.826)	(0.872)	(2.664)	(0.075)	(0.074)	(0.083)	(0.070)
R&DCut_Other	-0.009***	-0.008***	-0.007***	-0.026***	-0.153***	-0.134***	-0.098***	-0.429***	-0.003***	-0.004***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.019)	(0.018)	(0.017)	(0.060)	(0.001)	(0.001)	(0.001)	(0.001)
Benchmark	-0.001	-0.000	0.001	0.001	-0.012	-0.003	0.022*	0.007	0.003*	0.002	0.003*	0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.012)	(0.012)	(0.013)	(0.038)	(0.001)	(0.001)	(0.002)	(0.001)
JustMiss	-0.000	0.000	-0.000	0.000	-0.008	0.002	0.003	0.004	-0.000	-0.000	-0.001	-0.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.011)	(0.011)	(0.011)	(0.034)	(0.001)	(0.001)	(0.001)	(0.001)
Beat	0.001***	0.001***	0.001***	0.004***	0.006	0.011*	0.013**	0.052***	0.001	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.006)	(0.006)	(0.005)	(0.018)	(0.000)	(0.000)	(0.000)	(0.000)
R&D	0.001***	0.001***	0.001***	0.002***	0.009***	0.010***	0.009***	0.033***				
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.003)				
Assets	-0.002***	-0.002***	-0.002***	-0.006***	-0.035***	-0.030***	-0.026***	-0.121***	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.003)	(0.003)	(0.011)	(0.000)	(0.000)	(0.000)	(0.000)
MtoB	-0.000	0.000*	0.000***	0.000***	0.003***	0.004***	0.005***	0.014***	0.000**	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)
Cash	0.015***	0.015***	0.015***	0.047***	0.207***	0.196***	0.190***	0.690***	-0.000	0.001	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.004)	(0.022)	(0.022)	(0.021)	(0.079)	(0.001)	(0.001)	(0.001)	(0.001)
ROA	0.001	0.004***	0.006***	0.008**	0.051**	0.086***	0.104***	0.217***	0.001**	0.001**	0.002**	0.001***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.020)	(0.019)	(0.019)	(0.072)	(0.001)	(0.001)	(0.001)	(0.001)
BasicResearch	0.004***	0.004***	0.004***	0.012***	0.085***	0.069***	0.058***	0.228***	0.000**	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.003)	(0.003)	(0.011)	(0.000)	(0.000)	(0.000)	(0.000)
$Counts_t$	0.100***	0.087***	0.074***	0.275***								
	(0.013)	(0.011)	(0.010)	(0.034)								
$Cites_t$					0.019**	0.016**	0.014**	0.057**				
					(0.008)	(0.007)	(0.006)	(0.024)				
$Efficiency_t$									0.167***	0.159***	0.147***	0.147***
									(0.011)	(0.011)	(0.011)	(0.010)
Constant	0.025***	0.023***	0.020***	0.076***	0.496***	0.409***	0.347***	1.711***	0.001	0.001	-0.000	0.001
	(0.003)	(0.003)	(0.003)	(0.009)	(0.050)	(0.049)	(0.048)	(0.181)	(0.001)	(0.002)	(0.002)	(0.001)
Observations	72,963	70,524	68,121	68,121	72,963	70,524	68,121	68,121	72,963	70,524	68,121	68,121
R^2	28.12%	24.82%	21.59%	29.09%	22.91%	21.01%	19.44%	24.13%	17.26%	14.48%	13.51%	16.91%
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
***p*(*R&DCut_REM* = *R&DCut_Other*)**	**0.1776**	**0.0514**	**0.0213**	**0.0379**	**0.1057**	**0.0207**	**0.0092**	**0.0361**	**0.0030**	**0.0014**	**0.0038**	**0.0018**

This table reports the effects of REM on innovation. Our specifications are like those in Table 2, but also include two earnings performance variables: *Beat* (an indicator variable equal to one if the firm's change in ROA is greater than or equal to 1 percent, and zero otherwise), and *JustMiss* (an indicator variable equal to one if the firm's change in ROA is less than zero and greater than −1 percent, and zero otherwise). See the notes to Table 1 for other variable definitions. The time placer *t* is from 1987 to 2013, and we thus include patent data until 2014. We exclude financial and utility firms and firms with zero R&D expense. Industry-year fixed effects are included (at the year and Fama-French 12 industry levels). Robust firm-clustered standard errors are provided in parentheses below the coefficient value. *, **, and *** denote significant differences from zero at the 10 percent, 5 percent, and 1 percent levels, respectively.

TABLE 6

Effects of reversals in cuts

	$Counts_{t+1}$	$Counts_{t+2}$	$Counts_{t+3}$	$Counts_{t+1,t+3}$	$Cites_{t+1}$	$Cites_{t+2}$	$Cites_{t+3}$	$Cites_{t+1,t+3}$	$Efficiency_{t+1}$	$Efficiency_{t+2}$	$Efficiency_{t+3}$	$Efficiency_{t+1,t+3}$
R&DCut_REM	**-0.006**	**-0.008**	**-0.008**	**0.036**	**-0.483**	**-0.817**	**-0.857**	**-0.738**	**-0.214*** **	**-0.268*** **	**-0.248*** **	**-0.220*** **
	(0.044)	(0.046)	(0.052)	(0.131)	(1.095)	(1.051)	(1.100)	(3.354)	(0.083)	(0.077)	(0.092)	(0.074)
RevertIndicator	**-0.000**	**-0.001**	**-0.002**	**-0.007***	**0.028**	**-0.011**	**-0.009**	**-0.035**	**-0.003**	**-0.002**	**-0.005**	**-0.004**
	(0.001)	(0.001)	(0.001)	(0.003)	(0.032)	(0.030)	(0.035)	(0.092)	(0.003)	(0.004)	(0.004)	(0.003)
RevertIndicator×	**-0.113**	**-0.184*** **	**-0.218*** **	**-0.607*** **	**-3.345***	**-2.808**	**-3.983***	**-12.882*** **	**0.152**	**0.119**	**0.241**	**0.154**
R&DCut_REM	(0.075)	(0.085)	(0.093)	(0.243)	(1.957)	(1.855)	(2.097)	(6.120)	(0.166)	(0.188)	(0.178)	(0.167)
R&DCut_Other	-0.008***	-0.007***	-0.006***	-0.021***	-0.121***	-0.104***	-0.081***	-0.310***	0.000	0.001	-0.000	0.000
	(0.001)	(0.002)	(0.002)	(0.004)	(0.026)	(0.024)	(0.023)	(0.079)	(0.002)	(0.002)	(0.002)	(0.002)
Benchmark	-0.001**	-0.001	-0.000	-0.002	-0.022*	-0.014	0.010	-0.042	0.002	0.002	0.003*	0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.013)	(0.013)	(0.014)	(0.040)	(0.002)	(0.002)	(0.002)	(0.001)
R&D	0.000***	0.000***	0.000***	0.001***	0.008***	0.009***	0.007***	0.029***				
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.003)				
Assets	-0.002***	-0.001***	-0.001***	-0.005***	-0.033***	-0.026***	-0.024***	-0.110***	-0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.003)	(0.003)	(0.011)	(0.000)	(0.000)	(0.000)	(0.000)
MtoB	0.000	0.000**	0.000***	0.001***	0.004***	0.005***	0.005***	0.016***	0.000	0.000*	0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)
Cash	0.011***	0.013***	0.013***	0.038***	0.175***	0.184***	0.184***	0.642***	-0.000	0.001	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.004)	(0.024)	(0.024)	(0.024)	(0.084)	(0.001)	(0.001)	(0.001)	(0.001)
ROA	0.004***	0.005***	0.007***	0.013***	0.086***	0.098***	0.114***	0.258***	0.002**	0.002**	0.002*	0.002***
	(0.001)	(0.001)	(0.001)	(0.004)	(0.023)	(0.022)	(0.022)	(0.082)	(0.001)	(0.001)	(0.001)	(0.001)
BasicResearch	0.004***	0.004***	0.003***	0.011***	0.081***	0.067***	0.059***	0.223***	0.000	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.003)	(0.003)	(0.011)	(0.000)	(0.000)	(0.000)	(0.000)
$Counts_t$	0.173***	0.144***	0.129***	0.468***								
	(0.014)	(0.013)	(0.011)	(0.036)								
$Cites_t$					0.030***	0.026***	0.022***	0.090***				
					(0.008)	(0.007)	(0.006)	(0.025)				
$Efficiency_t$									0.178***	0.167***	0.151***	0.158***
									(0.020)	(0.020)	(0.020)	(0.018)
Constant	0.023***	0.019***	0.018***	0.069***	0.474***	0.352***	0.334***	1.597***	0.002	0.001	0.001	0.002
	(0.003)	(0.003)	(0.003)	(0.008)	(0.054)	(0.051)	(0.050)	(0.181)	(0.002)	(0.002)	(0.003)	(0.002)
Observations	36,042	34,865	33,857	33,857	36,042	34,865	33,857	33,857	36,042	34,865	33,857	33,857
R^2	32.29%	27.97%	25.47%	33.54%	24.58%	23.10%	21.69%	26.55%	16.85%	14.93%	12.92%	17.21%
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the effects of REM on innovation, controlling for the effects of reversed cuts. Our specifications are like those in Table 2 but also include an indicator for reversals in cuts: *RevertIndicator* (an indicator variable equal to one if the subsequent three-year growth in R&D intensity is above the sample mean, and zero otherwise). See the notes to Table 1 for definitions of other variables. The time placer *t* is from 1987 to 2013, and we thus include patent data until 2014. We exclude financial and utility firms, firms with zero R&D expense, and firms with negative one-year change in ROA. Industry-year fixed effects are included (at the year and Fama-French 12 industry levels). Robust firm-clustered standard errors are provided in parentheses below the coefficient value. *, **, and *** denote significant differences from zero at the 10 percent, 5 percent, and 1 percent levels, respectively.