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# Does Research and Development Activity Increase Accrual-Based Earnings Management?

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**Abstract**

Prior literature suggests that research and development (R&D) activity is associated with volatile earnings and that, in general, managers perceive earnings volatility as unfavorable and seek to avoid it. Accordingly, I hypothesize and find that the extent to which firms engage in R&D (R&D intensity) is positively associated with the extent to which they engage in accrual-based earnings management, as measured by discretionary accruals. I also find that greater R&D intensity is associated with a smaller positive effect of discretionary accruals on earnings volatility, suggesting that R&D intensity and discretionary accruals constitute non-additive sources of information uncertainty. This study provides empirical evidence of the prevalence of earnings management practices in R&D-intensive industries, supporting conjectures of regulators, practitioners, and academics.

**Keywords**

research and development (R&D), discretionary accruals, earnings management

## Introduction

Over the past decade, regulators, practitioners, and academics have noted the propensity of technology industries to engage in earnings management practices. Lev (2003), for example, states that a large number of earnings manipulations occur in the volatile high-tech and science-based sectors. In their survey, Graham, Harvey, and Rajgopal (2005) demonstrate strong executive preferences for smooth earnings, even at the expense of a certain loss of value. High-tech executives stand out in this regard, with 92.3% of those surveyed indicating a willingness to sacrifice value to avoid a bumpy earnings path (compared with 76.2% of the executives in other firms). Notably, prior research has not explored the relationship between research and development (R&D) activity and accrual-based earnings management, specifically, earnings smoothing.[1] Addressing this void, the current study hypothesizes and finds that the extent to which a firm engages in R&D is positively associated with the magnitude of discretionary accruals reported by the firm, an indicator of earnings

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management. In addition, it explores the relationship between R&D, discretionary accruals and stock return volatility, reflecting information uncertainty.

Prior research shows that the extent to which a firm engages in R&D activity is positively associated with the volatility of its earnings (Amir, Guan, & Livne, 2007; Chambers, Jennings, & Thompson, 2002; Dichev & Tang, 2009; Kothari, Laguerre, & Leone, 2002; Pandit, Wasley, & Zach, 2011). It also documents the unfavorable implications associated with high earnings volatility (Smith & Stulz, 1985; Trueman & Titman, 1988) and that executives associate smooth earnings with benefits for the firm (Graham et al., 2005). Taken together, these findings suggest that firms that engaged heavily in R&D have a greater need to engage in earnings management. Accordingly, I hypothesize that R&D intensity (defined as the ratio of R&D expenditures to sales) is positively correlated with earnings management, as reflected in discretionary accruals.

The empirical analysis, based on a sample spanning 23 years (1988-2010) and 77,003 firm-year observations, supports this hypothesis. A cross-sectional regression in which R&D intensity is evaluated as a predictor of absolute performance-matched discretionary accruals (following Kothari, Leone, & Wasley, 2005) yields a positive and highly significant coefficient of 0.019 ($p < .001$).[2] In light of concerns expressed by Hribar and Nichols (2007) regarding the use of unsigned measures of discretionary accruals to infer earnings management, I use their control variable approach. I also control for industry, as Dopuch, Mashruwala, Seethamraju, and Zach (2012) show that industry characteristics affect the cross-sectional estimation of absolute discretionary accruals (ADA). I carry out robustness checks using two alternative metrics of discretionary accruals: ADA (unmatched) and accruals quality (AQ), a measure based on Francis, LaFond, Olsson, and Schipper (2005). The coefficients on R&D intensity remain positive and highly significant in all specifications. Finally, I use the inverse smoothing measure introduced by Francis, LaFond, Olsson, and Schipper (2004), defined as the ratio of the standard deviation of net income to the standard deviation of cash flows from operations, as an additional measure of accrual-based earnings management.[3] Estimation results yield a negative R&D intensity coefficient, reflecting its positive impact on earnings smoothing. Taken together, these results indicate a positive correlation between R&D intensity and ADA, consistent with my hypothesis.

Next, I examine the relationship between R&D intensity, ADA, and stock return volatility. One stream of literature associates R&D outlays with poor information quality of financial reporting and with uncertainty regarding future earnings (Aboody & Lev, 2000; Barron, Byard, Kile, & Riedl, 2002; Barth, Kasznik, & McNichols, 2001; Ciftci, Lev, & Radhakrishnan, 2011; Matolcsy & Wyatt, 2006). Research also shows that poorer information quality translates into higher stock return volatility. Specifically, poor quality of financial reporting generates uncertainty about a firm's future profitability, and as stock prices are a function of expected future earnings, this uncertainty is likely to generate high volatility (Chen, DeFond, & Park, 2002; Diamond & Verrecchia, 1991; Healy, Hutton, & Palepu, 1999; Pastor & Veronesi, 2003). Hence, R&D intensity is expected to be positively correlated with stock return volatility. Prior literature indeed provides evidence for this correlation (Chambers et al., 2002; Chan, Lakonishok, & Sougiannis, 2001).

Another stream of literature uses discretionary accruals as a proxy for uncertainty and poor information quality (e.g., Aboody, Hughes, & Liu, 2005; Bhattacharya, Ecker, Olsson, & Schipper, 2012; Dechow & Dichev, 2002; Francis et al., 2005). Hence, discretionary accruals are expected to increase stock return volatility. In accordance with this view, Rajgopal and Venkatachalam (2011) argue that the deteriorating quality of financial reporting over recent decades, as reflected in accrual-based measures, is the reason for the rising stock return volatility documented by Campbell, Lettau, Malkiel, and Xu (2001).

I suggest that the poor financial reporting typically associated with R&D can affect the relationship between discretionary accruals and stock return volatility. As elaborated above, information uncertainty of R&D firms, and hence the volatility of their stock returns, are high to begin with. Given this fact, it is possible that the marginal uncertainty caused by discretionary accruals is smaller for firms that report R&D expenditures (hereafter referred to as R&D firms) than for firms that do not (non-R&D firms). If this is the case, discretionary accruals contribute to the stock return volatility of R&D firms less than they contribute to the volatility of non-R&D firms. Thus, my second hypothesis is that the impact of discretionary accruals on stock return volatility is lower for R&D firms relative to that of non-R&D firms.

In line with this hypothesis, I find that in a regression in which stock return volatility is the dependent variable, the coefficient of an interaction between R&D intensity and discretionary accruals is negative and significant. The findings are robust to regression specification. The meaning of these results is that stock return volatility becomes less sensitive to discretionary accruals as R&D intensity increases. Given the impact of R&D on information uncertainty, this finding indicates that discretionary accruals matter less to investors in R&D firms than to investors in non-R&D firms, as predicted.

The contribution of this study to the literature is twofold. First, it shows that the extent to which firms engage in R&D is positively correlated with the magnitude of these firms' discretionary accruals. To the best of my knowledge, this study is the first to empirically test the widely held belief that high-tech firms engage extensively in earnings management. These findings are particularly significant in light of the steady growth in R&D spending since the mid-1980s and the current importance of such spending as a productive input. The second contribution made by this study is the insight regarding the differential impact of discretionary accruals and the information uncertainty they impart on stock return volatility. The findings presented in this study are of interest to academics investigating R&D and its implications and to researchers examining discretionary accruals. They are also relevant to regulators interested in earnings management practices and to investors and practitioners analyzing financial reporting by R&D firms.

The remainder of the study proceeds as follows: Section ''Related Literature and Hypothesis Development'' reviews prior literature and develops the hypotheses. Section ''Research Design'' discusses methodology, and section ''Sample Selection and Descriptive Statistics'' describes the data. Section ''Empirical Results'' reports findings and section ''Concluding Remarks'' concludes.

## Related Literature and Hypothesis Development

In their seminal study, Graham et al. (2005) carried out a survey, which indicated that executives strongly prefer a smooth earnings path to a volatile one; an overwhelming 96.9% of respondents expressed such a preference. Moreover, most respondents admitted that they would sacrifice some degree of value to achieve a smoother earnings path. Executives in the high-tech industries—fields in which firms are very likely to engage in R&D—showed much greater willingness to sacrifice value to avoid a bumpy earnings path, compared with executives in other firms. This evidence suggests that managers of R&D firms have a greater propensity than do other managers to achieve earnings smoothness. Therefore, the practice of earnings management, specifically for the purpose of smoothing, may be more prevalent among R&D firms than among non-R&D firms. Articles in the popular press support this view, claiming that freewheeling accounting practices are widespread among high-tech firms.[4]

The penchant for earnings management practices in R&D firms may stem from the high earnings volatility generated by R&D activity, documented in prior literature. Within the context of the ongoing debate regarding capitalization versus expensing of R&D expenditures, Kothari et al. (2002) report that the future benefits generated by R&D investments are more volatile, and hence more uncertain than those generated by capital expenditures.[5] Amir et al. (2007) find that in R&D-intensive industries, the average contribution of R&D to the variability of subsequent operating income is greater than that of physical assets. In a similar vein, Chambers et al. (2002) show that earnings of ''high-R&D'' firms are more volatile than earnings of ''low-R&D'' firms and of ''non-R&D'' firms. Likewise, Dichev and Tang (2009) and Pandit et al. (2011) demonstrate a positive correlation between R&D intensity and earnings volatility. Taken together, all these findings suggest that R&D activity increases earnings volatility.

The literature shows that high earnings volatility is associated with unfavorable implications such as a high borrowing rate (Smith & Stulz, 1985; Trueman & Titman, 1988) and high tax liability (Smith & Stulz, 1985). Furthermore, Graham et al. (2005) report that executives associate smoother earnings with numerous benefits for the firm, such as lower costs of equity and debt, assurance to customers and suppliers that business is stable, and lower perceived risk by investors.

The positive relationship between R&D activity and earnings volatility, together with the detriments associated with such volatility, suggests that firms engaging in R&D have a greater incentive to engage in earnings management.

The literature examining the relationship between R&D and earnings management views R&D expenditures as an instrument, rather than a motivation, for real earnings management. For example, Roychowdhury (2006), Cohen, Dey, and Lys (2008), and Zang (2012) consider discretionary expenses, which include R&D expenditures, as one of three proxies for real earnings management. Gunny (2010) also identifies R&D expenditures as one of four means of real earnings management.

In light of the desirability of earnings management for R&D firms, managers of such firms consider whether to engage in accrual-based earnings management or real earnings management, including cutbacks in R&D spending.[6] Accrual-based earnings management may be preferable to real earnings management for several reasons. First and foremost, real earnings management may engender sub-optimal investment decisions and lead to a sacrifice of actual value. In contrast, accrual-based earnings management affects accounting records alone (Bens, Nagar, & Wong, 2002; Bhojraj, Hribar, Picconi, & McInnis, 2009; Cohen & Zarowin, 2010; Graham et al., 2005; Roychowdhury, 2006; Zang, 2012).[7] The potential loss of value stemming from real earnings management may be particularly damaging for firms with poor financial health (Zang, 2012), a quality characterizing many young R&D firms with negligible earnings. Moreover, financial models that do not take R&D assets and other intangibles into account may provide downward-biased estimates of the financial health of R&D firms, as compared with similar non-R&D firms.[8] This is yet another reason why R&D firms may be more sensitive to a loss of value. A second cost generated by real earnings management concerns tax credits. R&D tax credits encourage managers to invest more in R&D, in that they decrease the after-tax cost of R&D spending (Brown & Krull, 2008). Cutting R&D spending entails a loss of those credits, rendering such activity more costly. An additional consideration weighing against real earnings management through R&D spending is cost stickiness: Firms often incur asymmetric adjustment costs to remove resources and to restore them later if demand increases.[9] High adjustment costs make managers reluctant to downsize (Anderson, Banker, & Janakiraman, 2003). In many cases R&D is firm-specific, and personnel cannot be replaced easily; thus, adjustment costs are likely to be high, making R&D cutbacks less appealing than accrual-based earnings management. Finally, real earnings management decisions must be made prior to the end of the fiscal year, whereas accruals management can be executed after the fiscal year end, when the need for earnings management becomes most apparent. All these considerations encourage managers of R&D firms to prefer accrual-based earnings management over real earnings management.[10]

Accordingly, I posit that R&D outlays encourage accrual-based earnings management. As earnings can be managed either upward or downward to obtain a smooth earnings path, I use the absolute value of discretionary accruals as a proxy for earnings management. Using R&D intensity as a proxy for R&D activity, I hypothesize that

**Hypothesis 1 (H1):** R&D intensity is positively correlated with ADA.

Next, I examine the relationship between R&D intensity, ADA, and stock return volatility. A stream of literature associates R&D outlays with greater uncertainty regarding future earnings and with poor information quality in financial reporting. Aboody and Lev (2000) find that R&D contributes to information asymmetry and potential insider gains. Ciftci et al. (2011) also argue that R&D outlays increase information risk and asymmetry and hence generate mispricing. Focusing on analysts, Barth et al. (2001) report that information deficiency in financial reporting regarding intangible assets, primarily R&D assets, increases analyst coverage and effort. Barron et al. (2002) show that, compared with analysts who make forecasts for firms with few intangibles, analysts who conduct forecasts for intangible-intensive firms have a lower degree of consensus and larger forecast errors, attributable mostly to R&D activity. Matolcsy and Wyatt (2006) also investigate analyst coverage and forecast errors, finding that constraining the capitalization of intangibles reduces the usefulness of financial statements. In sum, prior research highlights R&D activity as a source of information uncertainty and asymmetry.

Research also shows that the quality of information in financial reporting is negatively associated with stock return volatility. The poorer the quality of a firm's financial reporting, the greater the uncertainty regarding the firm's future profitability is likely to be. Stock prices are a function of expected future earnings; therefore, greater uncertainty about future earnings is likely to generate higher volatility (Chen et al., 2002; Pastor & Veronesi, 2003). Furthermore, literature also holds that improvements in the level of disclosure and the quality of financial reporting mitigate information asymmetries about a firm's performance and reduce the volatility of stock returns (see Diamond & Verrecchia, 1991; Healy et al., 1999). Hence, R&D intensity is expected to be positively correlated with stock return volatility. Prior literature indeed documents such a correlation (Chambers et al., 2002; Chan et al., 2001).

In another stream of literature, discretionary accruals serve as a proxy for uncertainty and poor information quality (e.g., Aboody et al., 2005; Bhattacharya et al., 2012; Dechow & Dichev, 2002; Francis et al., 2005). Hence, the magnitude of discretionary accruals is expected to be positively associated with stock return volatility as well. Accordingly, Rajgopal and Venkatachalam (2011) argue that the deteriorating quality of financial reporting over recent decades, proxied by accrual-based measures, is a cause of the increase in stock return volatility documented by Campbell et al. (2001).

The question remains whether the same relationship between discretionary accruals and stock return volatility holds in R&D firms? As discussed above, the poor disclosure on R&D activity makes information uncertainty, and hence stock return volatility, high from the outset. Accordingly, it is possible that the incremental uncertainty generated by discretionary accruals does not have a salient impact on the return volatility of R&D firms. In other words, because of the uncertainty engendered in R&D activity, the marginal adverse effect of discretionary accruals is smaller for R&D firms than for non-R&D firms. If this is the case, discretionary accruals contribute to the stock return volatility of R&D firms less than they contribute to the stock return volatility of non-R&D firms. Therefore, I state the second hypothesis as follows:

**Hypothesis 2 (H2):** R&D intensity is associated with a lower degree of sensitivity to the effect of ADA on stock return volatility.

## Research Design

### *Metrics of Discretionary Accruals*

I use the absolute value of performance-matched discretionary accruals as the primary measure of earnings management, consistent with prior literature that employs unsigned measures of discretionary accruals in the absence of directional predictions. The use of this metric is based on the premise that earnings can be managed either upward or downward to meet current firm- and year-specific needs, such as smoother earnings (Graham et al., 2005).[11] Therefore, I measure unsigned discretionary accruals as a means of capturing both upward and downward earnings management.

I calculate the ADA for each firm-year, using the modified Jones model, as presented by Dechow, Sloan, and Sweeney (1995), in its cross-sectional version (see DeFond & Jiambalvo, 1994).[12] To derive the coefficients required for the estimation of firm-specific non-discretionary accruals, I regress total accruals against the change in revenues (adjusted for the change in receivables) and gross property plant and equipment. The regression model is estimated as follows for each year and two-digit Standard Industrial Classification (SIC) code grouping for which there are at least eight firm-year observations per regression:

$$\mathrm{TA}_{i,t} = \alpha_t + \beta_{1,t}\frac{1}{\mathrm{ASSETS}_{i,t-1}} + \beta_{2,t}\frac{\Delta\mathrm{REV}_{i,t} - \Delta\mathrm{REC}_{i,t}}{\mathrm{ASSETS}_{i,t-1}} + \beta_{3,t}\frac{\mathrm{PPE}_{i,t}}{\mathrm{ASSETS}_{i,t-1}} + \varepsilon_{i,t}, \tag{1}$$

where $\mathrm{TA}_{i,t}$ is firm $i$'s total accruals in year $t$, and is equal to earnings before extraordinary items and discontinued operations minus operating cash flows from continuing operations taken from the statement of cash flows; $\Delta\mathrm{REV}_{i,t}$ is the change in revenues between year $t-1$ and year $t$; $\Delta\mathrm{REC}_{i,t}$ is the change in receivables between year $t-1$ and year $t$; $\mathrm{PPE}_{i,t}$ is the gross value of property, plant, and equipment; and $\mathrm{ASSETS}_{i,t-1}$ is total assets at $t-1$. Detailed definitions of all variables used in this study are found in Table 1. I control for outliers by winsorizing the variables of the modified Jones model (ASSETS, PPE, or

**Table 1.** Variable Definitions.

| Variable (firm subscript *i* and year subscript *t* omitted) | Description (Compustat data items in parentheses) |
|---|---|
| ADA | Absolute discretionary accruals calculated using the modified Jones model. Normal accruals for each two-digit SIC code and year grouping are calculated as follows: $TA_{i,t} = \alpha_t + \beta_{1,t}\frac{1}{ASSETS_{i,t-1}} + \beta_{2,t}\frac{\Delta REV_{i,t}-\Delta REC_{i,t}}{ASSETS_{i,t-1}} + \beta_{3,t}\frac{PPE_{i,t}}{ASSETS_{i,t-1}} + \varepsilon_{i,t}.$ The coefficient estimates are used to estimate the firm-specific normal accruals. Absolute discretionary accruals are calculated as the absolute value of the difference between total accruals and the estimated normal accruals. |
| AGE | The natural logarithm of the number of years firm *i* has been publicly traded. |
| APMDA | Absolute performance-matched discretionary accruals, computed as ADA minus the median absolute discretionary accruals for the firm's corresponding industry-performance-matched portfolio, based on year, industry (two-digit Standard Industrial Classification [SIC] code), and lagged return-on-assets grouping. |
| AQ | Accruals quality based on Francis, LaFond, Olsson, and Schipper (2005), computed as the standard deviation of the residuals from a regression of firm *i*'s working capital accruals (total accruals minus depreciation and amortization) on cash flows from operations in the current period, previous period, and future period, PPE and change in revenues, calculated over years $t-4$ through *t*. |
| ASSETS | Total assets (Compustat $AT_t$) in millions of dollars. |
| BIG | A dummy variable equal to 1 if firm *i*'s auditing firm in year *t* is one of the Big 5 audit firms, 0 otherwise. |
| BV_MV | The ratio between firm *i*'s book value of equity (Compustat $CEQ_t$) and market value of equity (Compustat $PRCC\_F_t \times CSHO_t$). |
| CFO | Operating cash flows from continuing operations (Compustat $OANCF_t$-$XIDOC_t$) scaled total assets at the beginning of year *t* ($AT_{t-1}$). |
| DD | A dummy variable equal to 1 if firm *i* distributed a dividend in year *t*, 0 otherwise. |
| ERN | Earnings before extraordinary items (Compustat $IB_t$) scaled by total assets at the beginning of year *t* ($AT_{t-1}$). |
| LEV | Financial leverage equal to the sum of long-term debt (Compustat $DLTT_t$) and debt in current liabilities (Compustat $DLC_t$) divided by the sum of the long-term debt, debt in current liabilities, and market value of equity. |
| PPE | The gross value of property, plant, and equipment (Compustat PPEGT). |
| RDINT | R&D intensity equal to the ratio of R&D expenditures (Compustat $XRD_t$) to sales (Compustat $SALE_t$). |
| RDPMDA | The product of RDINT and APMDA. |
| ΔREC | Change in receivables (Compustat RECT) between year $t-1$ and year *t*. |

*(continued)*

**Table 1.** (continued)

| Variable (firm subscript $i$ and year subscript $t$ omitted) | Description (Compustat data items in parentheses) |
|---|---|
| $\Delta$REV | Change in revenues (Compustat SALE) between year $t-1$ and year $t$. |
| $RET^{ADJ}$ | Annual stock return adjusted according to the Fama–French three-factor model, computed over a 12-month period starting at the beginning of the 4th month, following the end of the fiscal year. |
| $RET^{RAW}$ | Raw annual stock return calculated over a 12-month period starting at the beginning of the 4th month, following the end of the fiscal year. |
| ROE | Income before extraordinary items (Compustat $IB_t$) divided by lagged book value of equity (Compustat $CEQ_{t-1}$). |
| SIZE | The natural logarithm of firm $i$'s market value of equity in year $t$, in millions of dollars, calculated as the product of the fiscal year-end closing share price (Compustat $PRCC\_F_t$) and common shares outstanding (Compustat $CSHO_t$). |
| SMOOTHNESS | Smoothing measure defined by Francis, LaFond, Olsson, and Schipper (2004) as the ratio between the standard deviation of firm $i$'s ERN and the standard deviation of its CFO, calculated over a 10-year window. |
| STDCASHREV | Standard deviation of cash-based revenues (Compustat SALE + $\Delta$RECT) deflated by total assets calculated over the period $t-5$ to $t-1$. |
| STDCFO | Standard deviation of firm $i$'s cash flow from operations (Compustat OANCF) deflated by total assets, calculated over the period $t-5$ to $t-1$. |
| STDROE | Standard deviation of firm $i$'s ROE calculated over the period $t-5$ to $t-1$. |
| TA | Total accruals, equal to earnings before extraordinary items and discontinued operations (Compustat IBC) minus operating cash flows from continuing operations taken from the cash flow statements (Compustat OANCF-XIDOC). |
| $VOL^{ADJ}$ | Monthly volatility of the Fama–French three-factor-adjusted stock returns, calculated over a 12-month period starting at the beginning of the fourth month, following the end of the fiscal year. |
| $VOL^{RAW}$ | Monthly volatility of raw stock returns, calculated over a 12-month period starting at the beginning of the fourth month, following the end of the fiscal year. |

$\Delta$REV − $\Delta$REC) at the extreme percentiles; that is, values less (greater) than the 1st (99th) percentile are set to be equal to the value of the 1st (99th) percentile.[13]

The coefficient estimates derived from Equation 1 are used to estimate the firm-specific non-discretionary accruals ($NA_{i,t}$) for each sample firm-year:[14]

$$\mathrm{NA}_{i,t} = \hat{\alpha}_t + \hat{\beta}_{1,t}\frac{1}{\mathrm{ASSETS}_{i,t-1}} + \hat{\beta}_{2,t}\frac{\Delta\mathrm{REV}_{i,t} - \Delta\mathrm{REC}_{i,t}}{\mathrm{ASSETS}_{i,t-1}} + \hat{\beta}_{3,t}\frac{\mathrm{PPE}_{i,t}}{\mathrm{ASSETS}_{i,t-1}}. \quad (2)$$

ADA is calculated as the absolute value of the difference between total accruals and the estimated non-discretionary accruals:

$$ADA_{i,t} = |TA_{i,t} - NA_{i,t}|. \quad (3)$$

I compute absolute performance-matched discretionary accruals using the approach suggested by Kothari et al. (2005). For each year and each industry, I form five portfolios by sorting the data into quintiles based on lagged return-on-assets. The absolute performance-adjusted discretionary accruals (APMDA) for each sample firm are composed of the firm-specific ADA minus the median ADA for the firm's corresponding industry-performance-matched portfolio, as in Klein (2002).

To check robustness, I use three alternative metrics for earnings management. The first one is ADA (unmatched to performance). The second is AQ, a measure introduced by Dechow and Dichev (2002) and modified by Francis et al. (2005). This measure reflects the extent to which working capital accruals map into operating cash flow realizations.[15] The cross-sectional model regresses working capital accruals (total accruals excluding depreciation expenses) against cash flows from operations in the current period, previous period, and future period, as well as variables from the modified Jones model, namely, PPE and change in revenues. The residuals derived from these annual cross-sectional regression estimations are the basis for the AQ metric: The AQ of firm *i* is defined as the standard deviation of firm *i*'s regression residuals ($\epsilon_{i,t}$) calculated over 5 years. AQ is an inverse measure of AQ, where the greater the standard deviation of residuals, the lower the quality of accruals and vice versa.[16]

The third alternative metric I use is the smoothing measure (SMOOTHNESS) defined by Francis et al. (2004) as the ratio of firm *i*'s standard deviation of net income before extraordinary items, divided by beginning total assets, to its standard deviation of cash flows from operations divided by beginning total assets. Smaller values of SMOOTHNESS indicate smoother earnings and vice versa. Similarly to Francis et al. (2004), the standard deviations are calculated over rolling 10-year windows. However, as R&D level can change significantly during such a long period, I also remeasure SMOOTHNESS over a 5-year period to check robustness.

## Testing H1

I use a cross-sectional regression model to test the relationship between R&D and discretionary accruals. Specifically, the model regresses APMDA on R&D intensity and control variables. The model also controls for annual fixed effects and industry controls. The specification is as follows:

$$\begin{aligned}\text{APMDA}_{i,t} = \alpha + \beta_1\text{RDINT}_{i,t} + \beta_2\text{SIZE}_{i,t} + \beta_3\text{BV\_MV}_{i,t} + \beta_4\text{LEV}_{i,t} + \beta_5\text{BIG}_{i,t} \\ + \beta_6\text{AGE}_{i,t} + \beta_7\text{STDCFO}_{i,t} + \beta_8\text{STDCASHREV}_{i,t} + \varepsilon_{i,t},\end{aligned} \tag{4}$$

where $\text{RDINT}_{i,t}$ denotes R&D intensity (the ratio of R&D expenditures to sales). The control variables used in the regression are as follows: $\text{SIZE}_{i,t}$ is the natural logarithm of firm $i$'s market value of equity in millions of dollars in year $t$; $\text{BV\_MV}_{i,t}$ is the ratio between firm $i$'s book value of equity and market value of equity; $\text{LEV}_{i,t}$ is the financial leverage of firm $i$ in year $t$, equal to the sum of long-term debt and debt in current liabilities divided by the sum of the long-term debt, debt in current liabilities, and the market value of equity; $\text{BIG}_{i,t}$ is a dummy variable equal to 1 if the firm auditing firm $i$ in year $t$ is one of the Big 5 audit firms, 0 otherwise; $\text{AGE}_{i,t}$ is the natural logarithm of the number of years in which firm $i$ has been publicly traded; $\text{STDCFO}_{i,t}$ is the standard deviation of cash flow from operations deflated by total assets, computed over the period $t - 5$ to $t - 1$; and $\text{STDCASHREV}_{i,t}$ denotes the standard deviation of cash-based revenues deflated by total assets, computed over the period $t - 5$ to $t - 1$. Definitions of all variables used in this study are found in Table 1.

I include STDCFO and STDCASHREV in the model in light of the concerns raised by Hribar and Nichols (2007) regarding the use of unsigned accrual measures to infer earnings management. Specifically, following the control variable approach proposed by Hribar and Nichols, I use these two variables to control for inherent operating volatility. The use of these variables reduces the sample size considerably, as they necessitate at least 7 consecutive years of available data. Therefore, the regression model is specified twice. The first specification does not include STDCFO and STDCASHREV as controls, and hence utilizes the entire sample; the second specification incorporates the two control variables, thus relying on a smaller sample of observations that meet data requirements (approximately 55% of the full sample). Both models control for industry, following the observations of Dopuch et al. (2012), which document how industry characteristics affect cross-sectional estimations of ADA. The statistical tests in both specifications are based on clustered standard errors at the firm level (Petersen, 2009).

Following H1, I anticipate the coefficient on RDINT to be positive and significant. In addition, in line with prior literature, the coefficient estimates of SIZE, BV_MV, LEV, BIG, and AGE are expected to be negative, whereas the coefficient estimates of STDCFO and STDCASHREV are expected to be positive (Butler, Leone, & Willenborg, 2004; Cohen et al., 2008; Doyle, Ge, & McVay, 2007; Hribar & Nichols, 2007).

To test robustness, I repeat the estimation of Equation 4 using the three alternative metrics of accrual-based earnings management (ADA, AQ, and SMOOTHNESS) as the dependent variables, instead of APMDA. All models control for industry and year effects and use clustered standard errors for statistical tests.

I also analyze the prevalence of earnings management among R&D firms. For this purpose, I partition the full sample into six categories based on R&D intensity, in ascending order. The first category consists of all non-R&D firm-years. All R&D firm-years are equally distributed across the remaining five R&D categories in ascending order of R&D intensity: Firm-years with the lowest (highest) R&D intensity are assigned to the second (sixth) R&D category. These five R&D categories are only roughly equal in size because they are formed using quintile cutoffs calculated for each year. Next, I identify each firm-year whose APMDA ranked in the top APMDA quintile for the corresponding year. I assume that earnings management is highly likely to have taken place in these firm-years (which I refer to as ''suspect firm-years''). Finally, for each R&D category, I compute the frequency of suspect firm-years, defined as the number of suspect firm-years in the category divided by the total number of firm-years in the category. In accordance with H1, I expect to find that the frequency of suspect firm-years increases with R&D intensity.

### Additional Robustness Checks—Simultaneity and Sub-Sample Analysis

Addressing the issue of the timing of earnings management activities, Zang (2012) discusses and provides empirical support for the sequential nature of real earnings management and accrual-based earnings management. In particular, real earnings management, such as cutbacks in R&D spending, must occur during the fiscal year, whereas accrual-based earnings management can also take place after the end of fiscal year. Nevertheless, there is still a possibility that managers simultaneously adjust R&D spending and distort accruals, indicating that Equation 4 could be limited by simultaneity issues.

I conduct two additional analyses to confirm the robustness of my findings to simultaneous accrual-based earning management and real earnings management through change in R&D expenditures. First, to control for simultaneity, I use the approach detailed in Lev and Sougiannis (1996). In particular, I estimate a two-stage least-squares regression in which the instrument for firm *i* is the average R&D intensity of the other firms sharing *i*'s four-digit SIC code (INDSTRY_RDINT). Second, I repeat the estimation of Equation 4 using the firm's R&D category allocation rather than R&D intensity as the explanatory variable. The justification for this approach is as follows: Because firms that engage in R&D generally depend on it for their development, I assume that cutbacks in R&D spending because of real earnings management are not drastic in most cases. Otherwise, managers may face significant long-term damage to activity. The high stickiness of R&D spending also supports the premise of limited changes in R&D expenditures. Therefore, even if managers engage in both types of earnings management contemporaneously, fluctuations in R&D spending are expected to be relatively small. Consequently, the R&D category affiliation of the firm is relatively robust to fluctuations in spending caused by real earnings management.

Another question that arises from the analysis of the full sample is whether a particular group of R&D firms drives the observed relationship between R&D and discretionary accruals. It is possible that young R&D firms, having no or small revenues, drive the results by recording extremely high accruals relative to the scope of their activity. To test whether this is the case, I investigate a variety of sub-samples in the following manner: I divide the entire sample into five quintiles according to three alternative parameters: market value of equity, sales growth, and age. Overall, this procedure yields 15 sub-samples of the full sample. I then repeat the estimation of Equation 4 for each sub-sample separately. This analysis reveals whether the results hold solely for a particular sub-sample of firms or hold consistently across all sub-samples.

### Testing H2

The second hypothesis of this study is that R&D intensity is associated with a lower degree of sensitivity to the effect of ADA on stock return volatility. To test this hypothesis, I utilize a cross-sectional regression model that includes RDINT, APMDA, and an interaction variable, denoted RDPMDA, as explanatory variables. The coefficient on RDINT is expected to be positive, reflecting the contribution of R&D intensity to stock return volatility.[17] The coefficient on APMDA is also expected to be positive, given the documented correlation between discretionary accruals, information problems, and stock return volatility (Aboody et al., 2005; Bhattacharya et al., 2012; Dechow & Dichev, 2002; Francis et al., 2005; Rajgopal & Venkatachalam, 2011). The interaction variable, RDPMDA, equal to the product of RDINT and APMDA, is the main focus of this analysis as it represents the effect of R&D on the correlation between discretionary accruals and stock return volatility. If the coefficient of RDPMDA equals 0, these factors do not interact, and discretionary accruals would affect stock return volatility for R&D firms and for non-R&D firms equally. Conversely, if the coefficient of RDPMDA is negative (positive), discretionary accruals contribute less (more) to the stock return volatility of R&D firms than to that of non-R&D firms. In accordance with H2, I predict a negative coefficient on RDPMDA. Thus, I estimate the following cross-sectional model:

$$\begin{aligned}\mathrm{VOL}_{i,t}^{ADJ} = {} & \alpha + \beta_1\mathrm{APMDA}_{i,t} + \beta_2\mathrm{RDINT}_{i,t} + \beta_3\mathrm{RDPMDA}_{i,t} + \beta_4\mathrm{SIZE}_{i,t} + \\ & \beta_5\mathrm{BV\_MV}_{i,t} + \beta_5\mathrm{LEV}_{i,t} + \beta_6\mathrm{ROE}_{i,t} + \beta_7\mathrm{STDROE}_{i,t} + \beta_8\mathrm{DD}_{i,t} + \\ & \beta_9\mathrm{AGE}_{i,t} + \beta_{10}\mathrm{RET}_{i,t} + \varepsilon_{i,t},\end{aligned} \tag{5}$$

where $\mathrm{VOL}_{i,t}^{ADJ}$ denotes the volatility of stock returns adjusted according to the Fama–French three-factor model, calculated over a 12-month period starting at the beginning of the 4th month following the end of the fiscal year; $\mathrm{ROE}_{i,t}$ is earnings before extraordinary items scaled by the lagged book value of equity; $\mathrm{STDROE}_{i,t}$ is the standard deviation of $\mathrm{ROE}_{i,t}$; $\mathrm{DD}_{i,t}$ is a dummy variable equal to 1 if firm *i* distributed a dividend in year *t*, 0 otherwise; $\mathrm{AGE}_{i,t}$ is the natural logarithm of the number of years firm *i* has been publicly traded; and $\mathrm{RET}_{i,t}$ is the annual return on stock of firm *i* adjusted according to the Fama–French three-factor model, calculated over a 12-month period starting at the beginning of the fourth month following the end of the fiscal year. I use these additional controls following prior research investigating stock return volatility (Pastor & Veronesi, 2003; Rajgopal & Venkatachalam, 2011). In line with prior studies, I expect the coefficient estimates of SIZE, BV_MV, ROE, DD, and AGE to be negative and the coefficient of STDROE to be positive, whereas I do not have a clear expectation for the direction of LEV and RET, owing to mixed results in prior studies.

The model controls for year- and industry-fixed effects. The statistical tests are based on clustered standard errors at the firm level (Petersen, 2009). To test robustness, I estimate three specifications of Equation 5 differing solely in controls (the third specification incorporating all controls). In addition, I use alternative specifications which use the standard deviation of raw stock returns ($\mathrm{VOL}_{i,t}^{\mathrm{RAW}}$) as a dependent variable. Correspondingly, in these specifications $\mathrm{RET}_{i,t}$ is computed as a raw annual return.

## Sample Selection and Descriptive Statistics

I obtained financial statement data from the Compustat annual industrial file, and I obtained stock return data from the Center for Research in Security Prices (CRSP) monthly stock returns file. I used accruals data from statements of cash flows, in accordance with the recommendation of Hribar and Collins (2002), who suggest that such data are preferable to accruals derived from balance sheets. As cash flow statements have been mandatory under the Statement of Financial Accounting Standard (SFAS) No. 95 of the Financial

Accounting Standards Board (FASB) since 1987, I collected accounting data spanning the period 1988 to 2010.[18]

I started with 133,799 firm-year observations with the data necessary to calculate total assets; property, plant, and equipment; revenues; market value of equity; book value of equity; cash flows from operations and earnings before extraordinary items and discontinued operations for the current year; and total assets for the preceding year (the latter for deflation purposes). I included only firm-years with strictly positive total assets and revenues. The sample excluded financial services firms (SIC codes between 6000 and 6499) because the model is not structured to reflect their activities, and software firms (SIC codes 7370-7372) because they are subject to a distinctive capitalization requirement under SFAS No. 86 (FASB, 1985). After excluding these firm-years, I was left with 117,920 firm-year observations. Observations with revenues of less than US$10 million or with a share price lower than US$1 were filtered from the sample to eliminate economically marginal firms, resulting in a sample of 90,520 observations. In addition, I required at least 8 observations in each two-digit SIC code grouping per year to calculate discretionary accruals and performance-matched discretionary accruals. This requirement yielded a sample of 89,834 firm-year observations. Finally, observations that did not have sufficient CRSP monthly return data to calculate raw stock returns, Fama–French three-factor adjusted stock returns, and stock return volatility were excluded. Stock returns were measured using compounded buy–hold returns, inclusive of dividends and other distributions, for a 12-month period starting at the beginning of the fourth month following the end of the fiscal year. The CRSP data availability filter reduced the sample to 77,003 firm-year observations. The sample used for robustness checks was smaller, due to the requirement of at least 5 years of data for the calculation of STDCFO, STDCASHREV, AQ, and SMOOTHNESS.

Panel A of Table 2 contains summary statistics for the entire sample, for all R&D firms, and for all non-R&D firms. Notably, all discretionary accruals metrics (APMDA, ADA, and AQ) demonstrate higher values (both mean and median) for R&D firms than for non-R&D firms. In addition, in line with prior literature, R&D firms are associated with lower values of book-to-market value of equity and lower financial leverage relative to non-R&D firms.

Panel B of Table 2 reports characteristics of R&D categories (sorted in ascending order of R&D intensity): mean and median R&D intensity, net income before extraordinary items and discontinued operations (ERN), operating cash flow (CFO), total accruals (TA), and APMDA. Both earnings and cash flow of the sixth R&D category, consisting of firms the most highly R&D-intensive, are substantially lower than the corresponding values for the other five R&D categories. Moreover, the sixth category is the only one that records negative values of earnings and cash flows, indicating a preponderance of small R&D firms that have not yet achieved earnings, or even revenues. As for APMDA, the mean values of the second and third categories (consisting of firms with low R&D intensity) are lower than the mean APMDA value of the first category (consisting of non-R&D firms). Yet, the median APMDA values of all three categories are very similar. For the fourth, fifth, and sixth categories, the mean and median APMDA values increase with category. Notably, the mean and median APMDA values of the sixth category (most R&D-intensive) are considerably larger than those of the other categories. Nevertheless, the absence of controls affecting discretionary accruals limits the ability to draw conclusions from these descriptive statistics.

Table 3 presents a correlation matrix. R&D intensity is negatively correlated with total assets, book-to-market value of equity, financial leverage, and return on equity.

**Table 2.** Descriptive Statistics and Characteristics of R&D Categories.

Panel A: Descriptive Statistics.

| | Full sample | | R&D firms | | Non-R&D firms | |
|---|---|---|---|---|---|---|
| Variable | Mean | Median | Mean | Median | Mean | Median |
| N | 77,003 | | 33,236 | | 43,767 | |
| RDINT | 0.0594 | — | 0.1376 | 0.0443 | — | — |
| APMDA | 0.0654 | 0.0388 | 0.0720 | 0.0435 | 0.0605 | 0.0352 |
| ADA | 0.0658 | 0.0413 | 0.0722 | 0.0448 | 0.0610 | 0.0390 |
| AQ | 0.0524 | 0.0374 | 0.0620 | 0.0446 | 0.0446 | 0.0330 |
| SMOOTHNESS | 1.4989 | 0.9577 | 1.4554 | 0.9883 | 1.5320 | 0.9285 |
| SIZE | 5.7073 | 5.6017 | 5.8615 | 5.6831 | 5.5902 | 5.5365 |
| BV_MV | 0.6542 | 0.5221 | 0.5717 | 0.4560 | 0.7169 | 0.5723 |
| LEV | 0.2492 | 0.1904 | 0.1734 | 0.1064 | 0.3068 | 0.2715 |
| BIG | 0.5405 | 1.0000 | 0.5196 | 1.0000 | 0.5564 | 1.0000 |
| AGE | 2.6510 | 2.6391 | 2.6884 | 2.6391 | 2.6227 | 2.5649 |
| ASSETS | 3,360.8377 | 296.9300 | 4,493.3339 | 229.6205 | 2,500.8371 | 346.7410 |
| ERN | 0.0229 | 0.0417 | 0.0054 | 0.0437 | 0.0361 | 0.0406 |
| CFO | 0.0798 | 0.0850 | 0.0644 | 0.0822 | 0.0915 | 0.0870 |
| TA | −0.0547 | −0.0510 | −0.0535 | −0.0481 | −0.0556 | −0.0530 |
| STDCFO | 0.0738 | 0.0506 | 0.0852 | 0.0563 | 0.0644 | 0.0465 |
| STDCASHREV | 0.2538 | 0.1599 | 0.2392 | 0.1649 | 0.2658 | 0.1551 |
| $VOL^{ADJ}$ | 0.1354 | 0.1145 | 0.1418 | 0.1203 | 0.1306 | 0.1102 |
| $VOL^{RAW}$ | 0.1380 | 0.1173 | 0.1467 | 0.1252 | 0.1314 | 0.1118 |
| $RET^{ADJ}$ | −0.2955 | −0.3847 | −0.2836 | −0.3844 | −0.3045 | −0.3849 |
| $RET^{RAW}$ | 0.0899 | −0.0016 | 0.1079 | −0.0061 | 0.0762 | 0.0021 |

*(continued)*

**Table 2.** (continued)

Panel A: Descriptive Statistics.

| | Full sample | | R&D firms | | Non-R&D firms | |
|---|---|---|---|---|---|---|
| Variable | Mean | Median | Mean | Median | Mean | Median |
| RDPMDA | 0.0063 | — | 0.0145 | 0.0015 | — | — |
| ROE | −0.0485 | 0.0995 | −0.1839 | 0.0906 | 0.0543 | 0.1049 |
| STDROE | 2.0813 | 0.1791 | 2.0201 | 0.1879 | 2.1290 | 0.1699 |
| DD | 0.4357 | — | 0.3824 | — | 0.4761 | — |

Panel B: Characteristics of R&D Categories—Earnings, Cash Flows, and Accruals.

| | | RDINT | | ERN | | CFO | | TA | | APMDA | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| R&D category | N | Mean | Median | Mean | Median | Mean | Median | Mean | Median | Mean | Median |
| 1 | 43,766 | — | — | 0.0362 | 0.0406 | 0.0915 | 0.0870 | −0.0556 | −0.0530 | 0.0605 | 0.0352 |
| 2 | 6,637 | 0.0056 | 0.0056 | 0.0536 | 0.0526 | 0.0951 | 0.0937 | −0.0443 | −0.0470 | 0.0565 | 0.0358 |
| 3 | 6,652 | 0.0192 | 0.0184 | 0.0446 | 0.0537 | 0.0945 | 0.0942 | −0.0447 | −0.0443 | 0.0558 | 0.0344 |
| 4 | 6,654 | 0.0468 | 0.0444 | 0.0404 | 0.0528 | 0.0907 | 0.0917 | −0.0464 | −0.0444 | 0.0654 | 0.0411 |
| 5 | 6,652 | 0.1029 | 0.0972 | 0.0321 | 0.0498 | 0.0793 | 0.0853 | −0.0490 | −0.0469 | 0.0790 | 0.0500 |
| 6 | 6,642 | 0.5136 | 0.2380 | −0.1441 | −0.0589 | −0.0376 | 0.0018 | −0.0834 | −0.0641 | 0.1032 | 0.0645 |

*Note*. Panel A summarizes descriptive statistics for the entire sample of R&D firms and non-R&D firms. "R&D firms" signify observations posting R&D expenditures. "Non-R&D" firms are all other observations. The sample consists of all firms in the Compustat annual database from 1988 to 2010, which meet the data requirements, excluding financial firms (SIC 6000-6499) and software firms (SIC 7370-7372). Observations with revenues less than 10 million dollars or with a share price below US$1 are deleted from the sample to eliminate economically marginal firms. In addition, each two-digit SIC code and year grouping is required to have at least eight observations. Panel B presents earnings, cash flows, and accruals for the R&D categories. The sample is partitioned into six categories based on R&D intensity, in ascending order. The first category consists of all non-R&D firm-years. All R&D firm-years are equally distributed into the remaining five categories in ascending order of R&D intensity: The least R&D-intensive firms are assigned to the Category 2, whereas the most R&D-intensive firms are found in Category 6. These five R&D categories are only roughly equal in size because they are formed using quintile cutoffs calculated for each year. For variable definitions, see Table 1.

**Table 3.** Correlation Matrix.

| Variable | RDINT | APMDA | ADA | AQ | SMOOTHNESS | SIZE | BV_MV | LEV | BIG | AGE | ASSETS | STDCFO | STDCASHREV | $VOL^{ADJ}$ | $RET^{ADJ}$ | RDPMDA | ROE |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| RDINT | 1.000 | .101* | .109* | .181* | .050* | .011* | −.086* | −.131* | .014* | −.084* | −.023* | .069* | −.013* | .118* | .014* | .648* | −.009* |
| APMDA | .117* | 1.000 | .872* | .465* | .093* | −.189* | −.071* | −.090* | −.037* | −.204* | −.075* | .123* | .084* | .260* | −.024* | .212* | −.023* |
| ADA | .094* | .687* | 1.000 | .482* | .095* | −.196* | −.057* | −.084* | −.035* | −.199* | −.077* | .122* | .085* | .269* | −.024* | .220* | −.017* |
| AQ | .257* | .383* | .401* | 1.000 | .117* | −.245* | −.060* | −.112* | −.062* | −.248* | −.097* | .192* | .333* | −.002 | −.196* | .285* | −.016* |
| SMOOTHNESS | .052* | .090* | .096* | .192* | 1.000 | −.043* | −.022* | −.006 | −.018* | −.488* | .002 | .030* | .025* | .141* | −.005 | .033* | .001 |
| SIZE | .033* | −.206* | −.225* | −.316* | −.044* | 1.000 | −.383* | −.160* | .034* | .276* | .386* | −.099* | −.117* | −.360* | .053* | .000 | .004 |
| BV_MV | −.170* | −.084* | −.067* | −.074* | −.079* | −.378* | 1.000 | .378* | −.009* | .003 | −.031* | −.031* | −.009 | .102* | .019* | −.048* | .003 |
| LEV | −.351* | −.125* | −.112* | −.164* | −.067* | −.094* | .324* | 1.000 | .048* | .070* | .072* | −.078* | −.029* | .065* | −.024* | −.064* | −.004 |
| BIG | −.035* | −.035* | −.033* | −.073* | −.025* | .042* | −.000 | .050* | 1.000 | −.011 | −.015* | −.020* | −.010* | −.037* | −.036* | .010* | −.004 |
| AGE | −.016* | −.193* | −.197* | −.279* | −.436* | .268* | .053* | .104* | −.011* | 1.000 | .145* | −.124* | −.114* | −.293* | .037* | −.051* | .004 |
| ASSETS | −.118* | −.266* | −.275* | −.376* | −.087* | .893* | −.084* | .252* | .058* | .332* | 1.000 | −.043* | −.040* | −.117* | .022* | −.014* | .002 |
| STDCFO | .193* | .295* | .290* | .538* | .102* | −.355* | −.056* | −.268* | −.060* | −.333* | −.454* | 1.000 | .271* | .120* | −.010* | .062* | −.001 |
| STDCASHREV | .048* | .188* | .196* | .374* | .058* | −.291* | −.006 | −.138* | −.019* | −.225* | −.332* | .560* | 1.000 | .119* | −.012* | .000 | −.001 |
| $VOL^{ADJ}$ | .134* | .278* | .291* | .430* | .188* | −.436* | .029* | −.012* | −.035* | −.372* | −.432* | .410* | .320* | 1.000 | .083* | .084* | −.004 |
| $RET^{ADJ}$ | −.008* | −.084* | −.087* | −.084* | −.041* | .169* | −.007* | −.043* | −.046* | .127* | .163* | −.087* | −.072* | −.155* | 1.000 | .005 | .003 |
| RDPMDA | .966* | .245* | .179* | .285* | .052* | .006 | −.166* | −.336* | −.035* | −.026* | −.141* | .209* | .068* | .153* | −.018* | 1.000 | −.018* |
| ROE | −.103* | −.080* | −.087* | −.203* | −.058* | .303* | −.308* | −.185* | .025* | .093* | .177* | −.105* | −.052* | −.266* | .097* | −.100* | 1.000 |

*Note.* Pearson's (Spearman's) correlations are presented above (below) the diagonal. Correlation coefficients that are statistically significant at the 5% level are presented with an asterisk. For variable definitions, see Table 1.

**Table 4.** Regressions of Absolute Performance-Matched Discretionary Accruals on R&D Intensity.

| | | APMDA | | APMDA | |
|---|---|---|---|---|---|
| Variable | Predicted sign | Estimate | *p* value | Estimate | *p* value |
| Intercept | | 0.1772 | <.0001 | 0.1615 | <.0001 |
| RDINT | + | 0.0186 | <.0001 | 0.0169 | <.0001 |
| SIZE | − | −0.0080 | <.0001 | −0.0070 | <.0001 |
| BV_MV | − | −0.0191 | <.0001 | −0.0160 | <.0001 |
| LEV | − | −0.0113 | <.0001 | −0.0018 | .4921 |
| BIG | − | −0.0038 | <.0001 | −0.0020 | .0274 |
| AGE | − | −0.0123 | <.0001 | −0.0103 | <.0001 |
| STDCFO | + | | | 0.0246 | .2564 |
| STDCASHREV | + | | | 0.0036 | .1492 |
| Adjusted $R^2$ (%) | | 11.80 | | 11.02 | |
| N | | 77,003 | | 42,511 | |

*Note.* This table presents coefficient estimates for the cross-sectional regressions of absolute performance-matched discretionary accruals, regressed on R&D intensity and control variables, using year- and industry-fixed effects. The statistical tests are based on clustered standard errors at the firm level (Petersen, 2009).
The full regression model is as follows:

$$\begin{aligned} \text{APMDA}_{i,t} = {} & \alpha + \beta_1\text{RDINT}_{i,t} + \beta_2\text{SIZE}_{i,t} + \beta_3\text{BV\_MV}_{i,t} + \beta_4\text{LEV}_{i,t} + \beta_5\text{BIG}_{i,t} \\ & + \beta_6\text{AGE}_{i,t} + \beta_7\text{STDCFO}_{i,t} + \beta_8\text{STDCASHREV}_{i,t} + \varepsilon_{i,t}. \end{aligned}$$

For variable definitions, see Table 1.

Conversely, R&D intensity is positively correlated with both cash flow volatility and stock return volatility. It is also positively correlated with all accruals metrics. The correlations among the various accruals metrics are noteworthy; specifically, APMDA and ADA are highly correlated (.687), and the correlation between APMDA and AQ is lower (.383). Finally, accrual metrics are negatively correlated with the market value of equity, financial leverage, age and total assets, and positively correlated with cash flow volatility and stock return volatility.

# Empirical Results

## H1 Results

This section reports results of the cross-sectional regressions testing whether R&D intensity is associated with discretionary accruals. Table 4 presents coefficient estimates for the regressions of APMDA on RDINT in two specifications: the first without and the second with controls for cash flow volatility. The results show that in both cases the coefficient on RDINT is positive and highly significant. In the first specification, applied to the entire sample, the coefficient on RDINT is 0.0186 ($p < .001$). In the second specification, which controls for operating volatility following Hribar and Nichols (2007), and therefore relies on a smaller sample, the coefficient on RDINT is 0.0169 ($p < .001$). Hence, incorporation of these controls does not change my results. These findings suggest that R&D is positively associated with discretionary accruals, as proposed in H1.[19] As for the control variables, the coefficient estimates are generally consistent with predictions the evidence cited in existing literature. SIZE, BV_MV, LEV, BIG, and AGE each have negative and significant coefficients.[20] Coefficient estimates on STDCFO and STDCASHREV are positive but insignificant.

Analyzing the economic significance of the relationship between R&D intensity and discretionary accruals, I compute discretionary accruals for different levels of R&D, based on the coefficient estimates and on mean values of the control variables. According to this analysis, an increase of 0.05 in R&D intensity is associated with an increase in discretionary accruals by approximately 3%. Hence, firms engaging in an average amount of R&D (i.e., R&D intensity corresponding to the mean of 0.138) can be expected to post discretionary accruals that are 8.1% higher, on average, than those of firms with similar characteristics which do not engage in R&D.

Table 5 presents the results of a battery of robustness checks. Panel A reports the estimation results after using alternative metrics for discretionary accruals. First, I repeat estimations of the cross-sectional regression model using ADA as the dependent variable. Coefficient estimates on RDINT remain positive and significant in both specifications, equal to 0.0194 ($p < .001$) in the first specification and 0.0167 ($p < .001$) in the second one. The second discretionary accruals measure I use to evaluate robustness is AQ. Again, the estimated coefficients on RDINT are positive and significant, equal to 0.0170 and 0.0169 in the first and second specifications, respectively ($p < .001$ for both). The third metric I utilize is SMOOTHNESS, where a negative coefficient sign on RDINT reflects a positive impact on earnings smoothing. Estimation results yield a small yet significant negative coefficient of −0.0003 ($p < .001$) for a 10-year measurement window and a coefficient of −0.0006 ($p = .0904$) for the 5-year window. Hence, the findings supporting H1 are robust for alternative discretionary accruals metrics.

Panel B of Table 5 reports the results of the simultaneity analyses. Using an instrumental variable approach, as in Lev and Sougiannis (1996), I find that the coefficient on the instrumental variable INDSTRY_RDINT in a two-stage least-squares regression remains positive and significant in both specifications. A second test substitutes the explanatory variable R&D intensity with R&D category, which is more robust to changes in R&D expenditures. Again, estimation results reveal a positive and significant coefficient on R&D category, as expected. In sum, these results indicate that the relationship between R&D and discretionary accruals is robust to simultaneous real earnings management (through changes in R&D spending) and accrual-based earnings management (through discretionary accruals).

Table 5 also contains the results of the sub-sample analyses. Panel C1 reports the results of Equation 4, estimated separately for each of five sub-samples, where observations are allocated to quintiles of market value of equity. Panels C2 and C3 report similar results for sub-samples based on age and sales growth, respectively. All 15 sub-samples demonstrate a positive and significant coefficient on R&D intensity, thus suggesting that the relationship between R&D and discretionary accruals is across the board and not limited to a certain group of R&D firms.[21]

I also reestimate the regression model separately for positive and negative discretionary accruals (reflecting income-increasing and income-decreasing earnings management, respectively), similarly to Myers, Myers, and Omer (2003) and Cohen et al. (2008). The results, reported in Table 6, show that the coefficient on RDINT is positive and significant for positive discretionary accruals and is negative and significant for negative discretionary accruals. Thus, R&D activity contributes to both types of earnings management.

The last analysis of H1 explores the prevalence of high discretionary accruals among R&D-intensive firms. For this purpose, I calculate the frequency of suspect firm-years

**Table 5.** Robustness Checks.

Panel A: Alternative Accrual-Based Measures.

| | | ADA | | ADA | | AQ | | AQ | | SMOOTHNESS 10Y | | SMOOTHNESS 5Y | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | Predicted sign | Estimate | *p* value | Estimate | *p* value | Estimate | *p* value | Estimate | *p* value | Estimate | *p* value | Estimate | *p* value |
| Intercept | | 0.1649 | <.0001 | 0.1611 | <.0001 | 0.1293 | <.0001 | 0.1258 | <.0001 | 3.2569 | <.0001 | 2.2113 | <.0001 |
| RDINT | +/−[a] | 0.0194 | <.0001 | 0.0167 | <.0001 | 0.0170 | <.0001 | 0.0169 | <.0001 | −0.0003 | <.0001 | −0.0006 | .0904 |
| SIZE | − | −0.0077 | <.0001 | −0.0068 | <.0001 | −0.0060 | <.0001 | −0.0055 | <.0001 | 0.0319 | <.0001 | 0.0633 | <.0001 |
| BV_MV | − | −0.0168 | <.0001 | −0.0140 | <.0001 | −0.0120 | <.0001 | −0.0108 | <.0001 | 0.0035 | .4742 | 0.0236 | .0893 |
| LEV | − | −0.0087 | <.0001 | −0.0027 | .2544 | −0.0007 | .7065 | 0.0013 | .5361 | 0.7364 | <.0001 | 1.0547 | <.0001 |
| BIG | − | −0.0030 | <.0001 | −0.0020 | .0195 | −0.0009 | .2346 | −0.0006 | .4342 | 0.0693 | .0028 | −0.0012 | 0.9660 |
| AGE | − | −0.0108 | <.0001 | −0.0087 | <.0001 | −0.0093 | <.0001 | −0.0090 | <.0001 | −0.5507 | <.0001 | −0.4006 | <.0001 |
| STDCFO | + | | | 0.0228 | .2406 | | | 0.0231 | .2620 | | | | |
| STDCASHREV | + | | | 0.0035 | .1405 | | | 0.0064 | .0418 | | | | |
| Adjusted $R^2$ (%) | | 12.19 | | 11.49 | | 23.06 | | 25.11 | | 18.34 | | 16.65 | |
| N | | 77,003 | | 42,511 | | 46,735 | | 41,184 | | 67,438 | | 67,438 | |

Panel B: Simultaneity Analysis.

| | | Instrumental variable approach | | | | R&D categories approach | | | |
|---|---|---|---|---|---|---|---|---|---|
| Variable | Predicted sign | Estimate | *p* value | Estimate | *p* value | Estimate | *p* value | Estimate | *p* value |
| Intercept | | 0.1740 | <.0001 | 0.1673 | <.0001 | 0.1623 | <.0001 | 0.1567 | <.0001 |
| INDSTRY_RDINT | + | 0.0378 | <.0001 | 0.0322 | <.0001 | | | | |
| RD_CATEGORY | + | | | | | 0.0050 | <.0001 | 0.0049 | <.0001 |
| SIZE | − | −0.0082 | <.0001 | −0.0071 | <.0001 | −0.0084 | <.0001 | −0.0074 | <.0001 |
| BV_MV | − | −0.0199 | <.0001 | −0.0169 | <.0001 | −0.0199 | <.0001 | −0.0167 | <.0001 |
| LEV | − | −0.0112 | <.0001 | −0.0007 | .8005 | −0.0073 | .0004 | 0.0025 | .3506 |
| BIG | − | −0.0039 | <.0001 | −0.0020 | .0402 | −0.0039 | <.0001 | −0.0020 | .0373 |
| AGE | − | −0.0128 | <.0001 | −0.0111 | <.0001 | −0.0125 | <.0001 | −0.0104 | <.0001 |

*(continued)*

**Table 5.** (continued)

Panel B: Simultaneity Analysis.

| | | Instrumental variable approach | | | | R&D categories approach | | | |
|---|---|---|---|---|---|---|---|---|---|
| Variable | Predicted sign | Estimate | $p$ value | Estimate | $p$ value | Estimate | $p$ value | Estimate | $p$ value |
| STDCFO | + | | | 0.0241 | .2589 | | | 0.0231 | .2671 |
| STDCASHREV | + | | | 0.0036 | .1521 | | | 0.0038 | .1349 |
| Adjusted $R^2$ | | 11.56% | | 10.85% | | 11.92% | | 11.23% | |
| N | | 71,018 | | 39,264 | | 77,003 | | 42,511 | |

Panel C1: Sub-Sample Analysis, Allocation Based on Market Value of Equity.

| Group | | 1 | | 2 | | 3 | | 4 | | 5 | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | Predicted sign | Estimate | $p$ value | Estimate | $p$ value | Estimate | $p$ value | Estimate | $p$ value | Estimate | $p$ value |
| Intercept | | 0.157 | <.0001 | 0.232 | <.0001 | 0.179 | <.0001 | 0.160 | <.0001 | 0.126 | <.0001 |
| RDINT | + | 0.036 | <.0001 | 0.018 | <.0001 | 0.010 | 0.003 | 0.020 | <.0001 | 0.036 | 0.029 |
| SIZE | − | −0.007 | <.0001 | −0.011 | <.0001 | −0.011 | <.0001 | −0.005 | 0.002 | −0.003 | <.0001 |
| BV_MV | − | −0.019 | <.0001 | −0.027 | <.0001 | −0.022 | <.0001 | −0.013 | <.0001 | −0.009 | 0.001 |
| LEV | − | −0.005 | 0.194 | −0.008 | 0.030 | −0.014 | 0.000 | −0.014 | 0.001 | −0.024 | <.0001 |
| BIG | − | −0.003 | 0.057 | −0.009 | <.0001 | −0.003 | 0.097 | −0.003 | 0.016 | 0.001 | 0.253 |
| AGE | − | −0.014 | <.0001 | −0.016 | <.0001 | −0.013 | <.0001 | −0.012 | <.0001 | −0.010 | <.0001 |
| Adjusted $R^2$ (%) | | 7.90 | | 9.60 | | 9.70 | | 10.60 | | 12.20 | |
| N | | 15,391 | | 15,405 | | 15,406 | | 15,405 | | 15,396 | |

Panel C2: Sub-Sample Analysis, Allocation Based on Age.

| Group | | 1 | | 2 | | 3 | | 4 | | 5 | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | Predicted sign | Estimate | $p$ value | Estimate | $p$ value | Estimate | $p$ value | Estimate | $p$ value | Estimate | $p$ value |
| Intercept | | 0.201 | <.0001 | 0.188 | <.0001 | 0.184 | <.0001 | 0.203 | <.0001 | 0.104 | <.0001 |
| RDINT | + | 0.019 | <.0001 | 0.012 | .000 | 0.014 | .003 | 0.038 | .000 | 0.178 | <.0001 |
| SIZE | − | −0.010 | <.0001 | −0.010 | <.0001 | −0.009 | <.0001 | −0.007 | <.0001 | −0.006 | <.0001 |
| BV_MV | − | −0.021 | <.0001 | −0.023 | <.0001 | −0.024 | <.0001 | −0.014 | <.0001 | −0.009 | <.0001 |
| LEV | − | −0.028 | <.0001 | −0.018 | <.0001 | −0.004 | .294 | −0.001 | .827 | 0.001 | .722 |

*(continued)*

**Table 5.** (continued)

Panel C2: Sub-Sample Analysis, Allocation Based on Age.

| Group | | 1 | | 2 | | 3 | | 4 | | 5 | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | Predicted sign | Estimate | *p* value | Estimate | *p* value | Estimate | *p* value | Estimate | *p* value | Estimate | *p* value |
| BIG | − | −0.008 | <.0001 | −0.006 | .001 | −0.002 | .262 | −0.002 | .117 | −0.000 | .902 |
| AGE | − | −0.017 | <.0001 | −0.011 | .049 | −0.017 | <.0001 | −0.020 | <.0001 | −0.000 | .980 |
| Adjusted $R^2$ | | 10.00% | | 9.90% | | 9.50% | | 9.50% | | 11.30% | |
| N | | 15,174 | | 15,602 | | 15,284 | | 15,468 | | 15,475 | |

Panel C3: Sub-Sample Analysis, Allocation Based on Sales Growth.

| Group | | 1 | | 2 | | 3 | | 4 | | 5 | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | Predicted sign | Estimate | *p* value | Estimate | *p* value | Estimate | *p* value | Estimate | *p* value | Estimate | *p* value |
| Intercept | | 0.169 | <.0001 | 0.121 | <.0001 | 0.108 | <.0001 | 0.142 | <.0001 | 0.246 | <.0001 |
| RDINT | + | 0.011 | <.0001 | 0.032 | <.0001 | 0.018 | <.0001 | 0.027 | <.0001 | 0.010 | .009 |
| SIZE | − | −0.009 | <.0001 | −0.006 | <.0001 | −0.006 | <.0001 | −0.008 | <.0001 | −0.010 | <.0001 |
| BV_MV | − | −0.020 | <.0001 | −0.010 | <.0001 | −0.011 | <.0001 | −0.017 | .009 | −0.025 | <.0001 |
| LEV | − | −0.002 | .565 | −0.003 | .348 | −0.005 | .115 | −0.010 | .001 | −0.032 | <.0001 |
| BIG | − | 0.000 | .814 | −0.004 | .000 | −0.004 | <.0001 | −0.004 | <.0001 | −0.006 | .001 |
| AGE | − | −0.009 | <.0001 | −0.007 | <.0001 | −0.005 | <.0001 | −0.007 | .652 | −0.012 | <.0001 |
| Adjusted $R^2$ (%) | | 11.10 | | 11.70 | | 10.50 | | 11.70 | | 10.60 | |
| N | | 15,391 | | 15,405 | | 15,402 | | 15,405 | | 15,396 | |

*Note*. The table reports the results of multiple robustness checks of Equation 4 (see Table 4): Panel A presents coefficient estimates for cross-sectional regressions of three alternative metrics of discretionary behavior (ADA, AQ, and SMOOTHNESS), regressed on R&D intensity and control variables. Panel B reports estimation results of two simultaneity analyses. The first set adopts an instrumental variable approach, as in Lev and Sougiannis (1996). The second set substitutes the explanatory variable R&D intensity with R&D category. Panels C1, C2, and C3 report analyses of various sub-samples. The full sample is allocated to five quintiles (in ascending order) based on three alternative parameters: market value of equity (Panel C1), sales growth (Panel C2), and age (Panel C3). The panels document results of estimations of Equation 4, quintile by quintile. All models control for year and industry. The statistical tests are based on clustered standard errors at the firm level (Petersen, 2009). For variable definitions, see Table 1.

[a]The predicted sign of the coefficients in the ADA and AQ regressions is positive, whereas the predicted sign in the SMOOTHNESS regressions is negative.

**Table 6.** Robustness Checks—Regressions of Positive Discretionary Accruals and Negative Discretionary Accruals on R&D Intensity.

| Variable | Predicted sign | Positive PMDA | | Negative PMDA | |
|---|---|---|---|---|---|
| | | Estimate | *p* value | Estimate | *p* value |
| Intercept | | 0.1423 | <.0001 | −0.1608 | <.0001 |
| RDINT | +/− | 0.0039 | .0596 | −0.0286 | <.0001 |
| SIZE | −/+ | −0.0070 | <.0001 | 0.0061 | <.0001 |
| BV_MV | −/+ | −0.0152 | <.0001 | 0.0147 | <.0001 |
| LEV | −/+ | −0.0116 | <.0001 | −0.0121 | .0009 |
| BIG | −/+ | −0.0030 | .0059 | 0.0008 | .4942 |
| AGE | −/+ | −0.0073 | <.0001 | 0.0108 | <.0001 |
| STDCFO | | 0.0124 | .3530 | −0.1443 | <.0001 |
| STDCASHREV | | 0.0055 | .1460 | 0.0050 | .0026 |
| Adjusted $R^2$ (%) | | 10.98 | | 14.11 | |
| N | | 21,972 | | 20,539 | |

*Note.* The table presents the coefficient estimates for the cross-sectional regressions of positive- and negative-performance-matched discretionary accruals, separately, as regressed on R&D intensity and various control variables. The model also controls for year and industry. The statistical tests are based on clustered standard errors at the firm level (Petersen, 2009). The model is presented in Table 4. Variable definitions: Positive PMDA is the value of positive-performance-matched discretionary accruals, computed using the modified Jones model. Negative PMDA is the value of negative-performance-matched discretionary accruals, computed using the modified Jones model. Other variable definitions are found in Table 1.

**Table 7.** Firms' Distribution Into Quintiles of Absolute Performance-Matched Discretionary Accruals.

| RD category | APMDA quintile | | | | | | |
|---|---|---|---|---|---|---|---|
| | 1 (%) | 2 (%) | 3 (%) | 4 (%) | 5 (%) | Total (%) | Δ(Q5 − Q1) (%) |
| 1 | 22 | 21 | 20 | 19 | 18 | 100 | −4 |
| 2 | 22 | 20 | 21 | 20 | 17 | 100 | −6 |
| 3 | 21 | 22 | 22 | 19 | 16 | 100 | −5 |
| 4 | 17 | 20 | 21 | 21 | 20 | 100 | 3 |
| 5 | 14 | 18 | 20 | 22 | 26 | 100 | 12 |
| 6 | 11 | 15 | 17 | 22 | 35 | 100 | 24 |

*Note.* Description of APMDA calculation is provided in Table 2. The full sample is partitioned into six R&D categories based on R&D intensity in ascending order, as detailed in Table 1. The sample is also divided into quintiles according to APMDA values. The allocation is based on yearly ranking, where the first quintile consists of all firms representing the lowest 20% APMDA values and the fifth quintile consists of those firm-years representing the highest 20%. Each row in the table presents the distribution of firm-years in the corresponding R&D category into APMDA quintiles. Δ(Q5 − Q1) is the difference between the percentage of firm-years in the fifth quintile and the percentage of firm-years in the first quintile.

(observations with APMDA ranked in the top quintile of the corresponding year) for each R&D category, equal to the number of suspect firm-years divided by the total number of firm-years in the category. In the absence of a correlation between R&D and earnings management, the frequency of suspect firm-years in each R&D category should be roughly 20% (one fifth of the observations in the category). Table 7 demonstrates, however, that this is not the case. The frequency of suspect firm-years is greater for R&D-intensive firms. In particular, 35% of the observations in the sixth R&D category (highest quintile in terms of R&D intensity) are suspect firm-years, well above the expected baseline level of 20%. This finding provides additional evidence of the relationship between R&D and discretionary accruals, indicating that the probability of a high level of earnings management is greater for R&D-intense firms.

### *H2 Results*

This section summarizes the results of cross-sectional regressions testing the effect of R&D intensity on the relationship between discretionary accruals and stock return volatility. Table 8 reports the estimated coefficients of the regression model in which stock return volatility is the dependent variable. Panel A presents the estimation results of the regression models using $VOL^{ADJ}$ as the dependent variable, utilizing different combinations of controls. Panel B presents results for corresponding specifications using $VOL^{RAW}$ as the dependent variable.

As reported in Panel A, the coefficient on RDINT is positive and significant in all specifications, ranging between 0.0249 and 0.0347 ($p < .001$ in all cases), reflecting the sensitivity of stock return volatility to R&D intensity. This finding is consistent with existing literature that associates R&D with stock return volatility (Chan et al., 2001; Chambers et al., 2002). The coefficient on APMDA is also positive and significant in all specifications, ranging between 0.1477 and 0.1756 ($p < .001$ in all cases). This result demonstrates the contribution of ADA to volatility, a finding that is consistent with prior research. Next, I examine RDPMDA, reflecting the interaction between R&D intensity and the magnitude of discretionary accruals on stock return volatility. Estimation results, reported in Panel A of Table 8, show a negative and significant coefficient on RDPMDA equal to −0.0484 in the first specification, −0.0322 in the second, and −0.0329 in the third ($p < .001$ for all specifications).

Panel B reports the corresponding results obtained when the dependent variable in the regression model is $VOL^{RAW}$. In all specifications, the coefficient on RDINT is positive and significant, and so is the coefficient on APMDA. The coefficient of RDPMDA remains negative and significant, as predicted. Taken together, the results show that the sensitivity of volatility to discretionary accruals decreases as R&D intensity increases. The findings suggest that given the effect of R&D on information uncertainty, discretionary accruals matter less to investors in R&D firms than to investors in non-R&D firms, thus supporting H2.

As a final point, both Panels A and B indicate that most of the controls used in the regression model have a robust impact on stock return volatility. The coefficients on SIZE, BV_MV, DD, and AGE are negative and significant in all specifications, whereas the coefficients on LEV, ROE, STDROE, and RET are positive and significant. The signs of the control coefficients are consistent with the existing literature (Pastor & Veronesi, 2003; Rajgopal & Venkatachalam, 2011).

## Concluding Remarks

Following the observations of regulators, academics, and practitioners during the past decade with respect to accrual-based earnings management practices prevailing among high-tech firms, this study investigates the relationship between R&D intensity and the use

**Table 8.** Regressions of Stock Return Volatility on R&D Intensity, Discretionary Accruals, and an Interaction Variable.

Panel A: Adjusted Stock Return Volatility.

| Variable | Predicted sign | Estimate | $p$ value | Estimate | $p$ value | Estimate | $p$ value |
|---|---|---|---|---|---|---|---|
| Intercept | | 0.1854 | <.0001 | 0.2384 | <.0001 | 0.2333 | <.0001 |
| RDINT | + | 0.0347 | <.0001 | 0.0249 | <.0001 | 0.0255 | <.0001 |
| APMDA | + | 0.1756 | <.0001 | 0.1477 | <.0001 | 0.1479 | <.0001 |
| RDPMDA | − | −0.0484 | <.0001 | −0.0322 | .0014 | −0.0329 | .0011 |
| SIZE | − | −0.0156 | <.0001 | −0.0124 | <.0001 | −0.0122 | <.0001 |
| BV_MV | − | −0.0103 | <.0001 | −0.0075 | <.0001 | −0.0073 | <.0001 |
| LEV | ? | 0.0344 | <.0001 | 0.0359 | <.0001 | 0.0353 | <.0001 |
| ROE | − | | | 0.0000 | .0329 | 0.0000 | .1270 |
| STDROE | + | | | 0.0014 | <.0001 | 0.0015 | <.0001 |
| DD | − | | | −0.0229 | <.0001 | −0.0232 | <.0001 |
| AGE | − | | | −0.0116 | <.0001 | −0.0106 | <.0001 |
| $RET^{ADJ}$ | ? | | | | | 0.0170 | <.0001 |
| Adjusted $R^2$ (%) | | 29.85 | | 32.27 | | 33.59 | |
| N | | 76,949 | | 64,629 | | 63,189 | |

Panel B: Raw Stock Return Volatility.

| Variable | Predicted sign | Estimate | $p$ value | Estimate | $p$ value | Estimate | $p$ value |
|---|---|---|---|---|---|---|---|
| Intercept | | 0.1738 | <.0001 | 0.2357 | <.0001 | 0.2300 | <.0001 |
| RDINT | + | 0.0366 | <.0001 | 0.0268 | <.0001 | 0.0273 | <.0001 |
| APMDA | + | 0.1773 | <.0001 | 0.1499 | <.0001 | 0.1521 | <.0001 |
| RDPMDA | − | −0.0465 | <.0001 | −0.0300 | .0031 | −0.0306 | .0022 |
| SIZE | − | −0.0130 | <.0001 | −0.0097 | <.0001 | −0.0094 | <.0001 |
| BV_MV | − | −0.0092 | <.0001 | −0.0060 | <.0001 | −0.0063 | <.0001 |
| LEV | ? | 0.0375 | <.0001 | 0.0400 | <.0001 | 0.0394 | <.0001 |
| ROE | − | | | 0.0000 | .0089 | 0.0000 | .0446 |
| STDROE | + | | | 0.0011 | <.0001 | 0.0012 | <.0001 |
| DD | − | | | −0.0240 | <.0001 | −0.0242 | <.0001 |
| AGE | − | | | −0.0113 | <.0001 | −0.0104 | <.0001 |
| $RET^{RAW}$ | ? | | | | | 0.0165 | <.0001 |
| Adjusted $R^2$ (%) | | 27.24 | | 29.64 | | 31.68 | |
| N | | 76,949 | | 64,629 | | 63,189 | |

*Note.* This table reports coefficient estimates from the cross-sectional regressions of stock return volatility on R&D intensity, on APMDA, and on the interaction variable RDPMDA. All specifications include controls and account for year-fixed effects. The statistical tests are based on clustered standard errors at the firm level (Petersen, 2009). Panel A presents the estimation results of the regressions using the volatility of the Fama–French three-factor-adjusted returns ($VOL^{ADJ}$) as a dependent variable, and Panel B presents robustness checks using the volatility of raw returns ($VOL^{RAW}$) as the dependent variable. The full regression model is as follows:

$$\begin{aligned} VOL_{i,t} = {} & \alpha + \beta_1 APMDA_{i,t} + \beta_2 RDINT_{i,t} + \beta_3 RDPMDA_{i,t} + \beta_4 SIZE_{i,t} + \beta_5 BV\_MV_{i,t} \\ & + \beta_5 LEV_{i,t} + \beta_6 ROE_{i,t} + \beta_7 STDROE_{i,t} + \beta_8 DD_{i,t} + \beta_9 AGE_{i,t} + \beta_{10} RET_{i,t} + \varepsilon_{i,t}. \end{aligned}$$

For variable definitions, see Table 1.

of discretionary accruals. Employing cross-sectional regressions, I find that R&D intensity is positively correlated with the magnitude of discretionary accruals, a proxy for accrual-based earnings management. This finding is robust for numerous accrual metrics, as well as for the incorporation of control variables and sample restrictions.

Additional analysis tests the relationships between R&D intensity, discretionary accruals, and stock return volatility. Cross-sectional regressions reveal that R&D intensity is negatively associated with the extent to which discretionary accruals affect volatility. These results suggest that, given the effect of R&D on information uncertainty, the marginal adverse impact of discretionary accruals is less important to investors in R&D firms than to investors in non-R&D firms.

My study contributes to the literature by providing evidence of the relationship between R&D and discretionary accruals and of the relative impact of discretionary accruals on the volatility of returns on R&D firms and non-R&D firms. These findings are of interest to academics investigating R&D and its consequences and to researchers examining discretionary accruals. They are also relevant to regulators interested in earnings management practices and to investors and practitioners analyzing the financial reporting by R&D firms.

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## Notes

1. Previous studies use R&D expenditures as one of the proxies for real earnings management (Cohen, Dey, & Lys, 2008; Gunny, 2010; Roychowdhury, 2006; Zang, 2012). However, they overlook the impact of R&D expenditures on the desire for earnings management.
2. I measure absolute discretionary accruals because earnings can be managed either upward or downward to obtain a smooth earnings path. My approach is in line with vast prior literature that uses unsigned discretionary accruals measures in the absence of a directional prediction. See Bartov, Gul, and Tsui (2001); Bergstresser and Philippon (2006); Doyle, Ge, and McVay (2007); Gul, Fung, and Jaggi (2009); Klein (2002), Myers, Myers, and Omer (2003); Reynolds and Francis (2000); Rajgopal and Venkatachalam (2011); Warfield, Wild, and Wild (1995).
3. Smaller (larger) values of this measure indicate more (less) earnings smoothness.
4. See, for example, the *New York Times*: ''Although the companies currently under federal investigation . . . are not from Silicon Valley, critics say many of the freewheeling practices that contributed to their problems are endemic in the Valley'' (Richtel, 2002).

5. They find that the impact of R&D expenditures on future earnings variability is about 3 times that of capital expenditures.
6. Of course, managers do not have to use one type of earnings management exclusively, but can engage in both types in the same fiscal year.
7. Yet, there is some contradicting evidence arguing that real earnings management does not damage future performance (Gunny, 2010).
8. See Franzen, Rodgers, and Simin (2007).
9. Adjustment costs include, for example, severance pay when employees are dismissed and search and training costs when new employees are hired.
10. Notably, accrual-based earnings management also has costs as it exposes the firm and the managers to sanctions and litigation. In addition, accounting choices are subject to auditor scrutiny, while operating decisions are controlled solely by management.
11. The literature reveals additional motivations for downward earnings management that are applicable to R&D firms. These motivations include the grant or repricing of employee stock options (Balsam, Chen, & Sankaraguruswamy, 2003; Callaghan, Saly, & Subramaniam, 2004; Coles, Hertzel, & Kalpathy, 2006; McAnally, Srivastava, & Weaver, 2008). Employee stock options are more prevalent among R&D firms than in other firms, as demonstrated by the industry composition of samples in prior research. Another instance of downward earnings management involves in-process R&D write-offs (Dowdell & Press, 2004; Nelson, Elliott, & Tarpley, 2002).
12. Original model was articulated in Jones (1991).
13. To alleviate concerns that results are driven by the immediate expensing of R&D expenditures, as an additional robustness check I estimate discretionary accruals by adjusting the balance sheets to reflect capitalization of R&D expenditures. Following prior literature (Chambers, Jennings, & Thompson, 2002; Chan, Lakonishok, & Sougiannis, 2001; Lev, Sarath, & Sougiannis, 2005), I estimate the R&D asset that would have been reported if all R&D outlays were capitalized and amortized over a period of 5 years. This R&D asset is added to the stated total assets in the modified Jones model. I do not adjust the stated PPE to reflect R&D assets as PPE is incorporated into the model as a generator of accruals (depreciation). Conversely, R&D expenditures are expensed immediately, and hence do not create accruals.
14. R&D expenditures are not expected to be correlated with non-discretionary accruals. The main generators of accruals are depreciation on PPE and change in working capital. Accordingly, these variables are the parameters in the modified Jones model used to estimate the level of non-discretionary accruals based on the firm's activity. R&D expenditures do not generate accruals as they are expensed immediately. For this reason, they are also not included as a parameter in the modified Jones model. Hence, R&D expenditures do not affect either actual accruals or estimated non-discretionary accruals. A correlation analysis confirms that non-discretionary accruals are not correlated with R&D intensity. The correlation coefficient is $-.003$ (statistically insignificant), supporting the assertion of independence.
15. Recent literature notes limitations of this measure. Wysocki (2008) presents evidence on the limited ability of accruals quality (AQ) to distinguish between manipulated and high-quality earnings. In particular, this measure is problematic when managers' discretionary accrual choices are correlated with the measurement error components of operating cash flows. Dechow, Ge, and Schrand (2010) also note that further research is needed to evaluate the power of this measure to identify discretionary accruals.
16. If a firm has consistently large residuals, the standard deviation of those residuals is small; thus, this firm has relatively good accruals quality. The reason for this phenomenon is that the poor mapping of accruals into cash flows is expected for this firm; therefore, there is little uncertainty as to the accruals.
17. A positive correlation between R&D and stock return volatility is also documented in Chan et al. (2001) and Chambers et al. (2002).

18. Valid statement-of-cash-flow data for the year 1987 are available for a relatively small number of firms, not enough to conduct a meaningful analysis at the industry level. For this reason, I do not use 1987 data.
19. Untabulated results confirm that the results also hold when adjusting total assets to reflect capitalization of R&D expenditures.
20. The coefficient on LEV is insignificant in the second specification.
21. For brevity, I report results of the first specification only (not including STDCFO and STDCASHREV as controls). Estimation of the second specification yields similar results (not tabulated).

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