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Cross-Sectional Determinants of Analyst Coverage for R&D Firms

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Abstract: Prior research document a positive association between analyst coverage and R&D. However, they do not investigate what particular attribute of R&D leads to this positive association. In this study we aim to fill the gap in the extant literature and explore the cross-sectional determinants of the association between R&D and analyst coverage. We investigate four cross-sectional determinants: reporting biases arising from expensing of R&D compared to capitalization of R&D, uncertainty associated with R&D, investors' attention, and scale effects of R&D. We find that while reporting biases and uncertainty decrease analyst coverage for R&D firms, investors' attention and scale effects of R&D increase analyst coverage. Furthermore, we find that the positive association between R&D and analyst coverage documented by Barth et al. is fully explained by scale effects of R&D.

Keywords: analyst coverage; reporting biases; expensing vs. capitalization of R&D; uncertainty; scale effects of R&D; investors' attention

JEL Classification: M41; G12; O3

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1. Introduction

Financial analysts are one of the most important information intermediaries between investors and firms. Consistent with this notion, prior research suggests that increase in analyst coverage leads to increase in stock liquidity and institutional ownership and decrease in the cost of equity (Beyer et al. 2010). Barth et al. (2001) suggest that firms with substantial intangible assets (e.g., R&D), most of which are not recognized in financial statements, have more information asymmetry and inherent uncertainty about firm value than other firms. They further argue that in the absence of private information acquisition by analysts, share prices of intangible-intensive firms would less precisely reflect their fundamental values, which will in turn create opportunities for private information acquisition for analysts. Consistent with these arguments, Barth et al. (2001) predict and find a positive association between analyst coverage and R&D. However, Barth et al. (2001) do not investigate what particular attribute of R&D leads to this positive association. In this paper we aim to bridge this gap in the extant literature and investigate cross-sectional determinants of analyst coverage for R&D firms. We explore four cross-sectional determinants: reporting biases arising from expensing of R&D compared to capitalization of R&D, uncertainty associated with R&D, investors' attention and scale effects of R&D.

The first cross-sectional determinant of analyst coverage for R&D firms is reporting bias arising from immediate expensing of R&D compared to capitalization of R&D. Prior research suggests that, due to immediate expensing of R&D, financial statements are less informative for R&D firms because accounting numbers do not reflect firm value and performance (Amir and Lev 1996; Lev and Zarowin 1999). An alternative source of information are the analyst forecasts. Kimbrough (2007) suggests that financial analysts might fill up the information gap (lack of informativeness) in the financial statements resulting from expensing of R&D. Analysts could benefit from private information acquisition by eliminating the information gap in the financial statements caused by reporting biases and increase analyst coverage for R&D firms. Consistent with this argument, Barth et al. (2001) suggest that immediate expensing of R&D increases information asymmetry for R&D firms, which leads to greater analyst coverage for these firms. Alternatively, reporting biases arising from expensing of R&D might also have the opposite effect on analyst coverage for R&D firms. Lang and Lundholm (1996) suggest that analyst coverage is greater (smaller) for firms with more (less) informative disclosures, because information acquisition costs are smaller (greater) for firms with more (less) informative disclosures. Reporting bias resulting from expensing of R&D is likely to reduce informativeness of financial statements and increase analysts' information acquisition costs, which could negatively affect analysts' willingness to follow R&D firms. Consequently, there are two competing hypotheses about the impact of reporting biases resulting from expensing of R&D on analyst coverage for R&D firms. Therefore, we do not have, a priori, a clear prediction about the impact of reporting biases on analyst coverage for R&D firms.

The second cross-sectional determinant of analyst coverage for R&D firms is uncertainty associated with R&D. Prior research suggests that future benefits of R&D are more uncertain than other investments (Lev 2001). The success rate of innovation activities is often very low, and the distribution of payoffs is highly skewed (Lev 2001). Consistent with these arguments, Kothari et al. (2002) document the fact that volatility of earnings for R&D is much greater than that for capital or advertising expenditures. Greater uncertainty associated with R&D may increase investors' demand for analyst forecasts. Therefore, greater uncertainty may increase analyst coverage for R&D firms. However, greater uncertainty associated with R&D could also increase analysts' forecast errors, and in turn decrease analyst coverage for R&D firms (Weiss 2010). Consequently, there are two competing hypotheses about the impact of uncertainty on the relationship between R&D and analyst coverage. Therefore, we do not have a clear prediction about the impact of uncertainty on analyst coverage for R&D firms.

The third cross-sectional determinant of analyst coverage for R&D firms is investor's attention. Owen (2002) suggests that investment in high-technology companies boomed as people invested large sums of money, even when there was little chance of the company being profitable. If investors direct greater attention toward R&D-intensive firms, this could also affect analyst coverage for these firms. Investment banks that hire financial analysts profit from trading commissions generated from stock trades. Consequently, financial analysts might follow R&D-intensive firms, which might increase trading commissions for their employer. Therefore, we expect investors' attention to increase analyst coverage for R&D intensive firms.

The last cross-sectional determinant of analyst coverage for R&D firms are the scale effects of R&D. Schumpeter (1942) suggests that larger firms are better positioned than smaller firms to implement and successfully exploit R&D efforts. Henderson and Cockburn (1996) argue that larger firms enjoy multiple R&D project spillover advantages. Cohen and Klepper (1996) suggest that larger firms have "cost spreading" advantages in R&D investment. Consistent with these arguments, Ciftci and Cready (2011) document the fact that R&D is associated with greater earnings for larger firms than for smaller firms, suggesting that larger R&D firms are more productive than smaller firms. Given that larger firms have more productive R&D, analyst coverage could be greater for larger R&D firms, because analyst are more likely to cover more R&D-productive firms. Therefore, we expect the scale effect of R&D to increase analyst coverage for R&D firms.

We use I/B/E/S, CRSP and Compustat data from the U.S. over the period of 1985 to 2018. Consistent with Barth et al. (2001), we use R&D-expense-to-operating-expense ratio as our measure of R&D intensity. We first investigate the impact of reporting biases from expensing of R&D compared to capitalization of R&D on analyst coverage for R&D firms. We use two proxies for reporting biases from expensing of R&D. The first proxy comes from Lev et al. (2005), and is based on the difference between return on equity

(ROE) and annualized R&D growth (RDG_ROE). We develop the second proxy on our own, based on the bias in earnings under expensing of R&D compared to capitalization of R&D (DIFROA). We separate firm-year observations into three categories based on reporting biases resulting from expensing of R&D: aggressive (conservative) firms are those in the bottom (top) 25% of measures of reporting bias (RDG_ROE and DIFROA) and neutral firms are those between 25% and 75% of measures of reporting bias. With the first measure of reporting bias (RDG_ROE), we find that the association between R&D and analyst coverage is lower for conservative firms compared to neutral firms. However, there is no statistically significant difference between aggressive and neutral firms in the association between R&D and analyst coverage.

These results suggest that while aggressive reporting has no impact on the association between analyst coverage and R&D, conservative reporting decreases this association. That is, conservative reporting leads to lower analyst coverage for R&D firms, while aggressive reporting has no effect on analyst coverage. Using the second measure of reporting bias resulting from expensing of R&D (i.e., DIFROA), we find that the association between R&D and analyst coverage for aggressive and conservative firms is significantly lower than that for neutral firms. That is, both conservative and aggressive reporting lead to a decrease in analyst coverage for R&D firms compared to neutral reporting. These results suggest that the costs associated with reporting biases from expensing of R&D are greater for financial analysts than the benefits arising from private information acquisition. Overall, our findings suggest that reporting biases from expensing of R&D negatively affect analyst coverage for R&D firms and that the impact is stronger for conservatively reporting firms than for aggressively reporting firms. Moreover, we find that reporting biases from expensing of R&D do not seem to explain the positive association between R&D and analyst coverage documented by Barth et al. (2001).

Second, we investigate the impact of the uncertainty associated with R&D on analyst coverage for R&D firms. We use two proxies for uncertainty: standard deviation of earnings over the past five years (from year t to $t-4$) and standard deviation of stock returns over fiscal year t. With both proxies, we find that the association between R&D and analyst coverage decreases with the uncertainty, suggesting that costs associated with the uncertainty for financial analysts outweigh the benefits. Moreover, we find that the uncertainty associated with R&D does not explain the positive association between R&D and analyst coverage.

Third, we investigate the impact of investors' attention on analyst coverage for R&D firms. We use trading volume as a proxy for investors' attention, following Barber and Odean (2008) and Hou et al. (2009). Trading volume is commonly used in financial literature as an indicator of investor interest because higher trading volumes typically reflect greater market activity and interest in a particular stock. Prior research has revealed that trading volume correlates strongly with investors' attention, making it a reliable proxy. We find that the association between R&D and analyst coverage increases with trading volume, suggesting that investors' attention increases analyst coverage for R&D firms. Furthermore, we find that investors' attention partially explain the positive association between R&D and analyst coverage, but not fully.

Fourth, we investigate the impact of scale effects of R&D on analyst coverage for R&D firms. We use log of firm size to capture the scale effects of R&D and find that the association between R&D and analyst coverage increases with firm size, suggesting that scale effects of R&D increase analyst coverage for R&D firms. Moreover, we find that scale effects of R&D fully explain the positive relationship between R&D and analyst coverage documented by Barth et al. (2001).

Finally, we investigate the combined effect of all cross-sectional determinants (i.e., combined effect of reporting biases, uncertainty, investors' attention and scale effects of R&D) on analyst coverage for R&D firms. We find that the association between R&D and analyst coverage decreases with reporting biases and uncertainty, consistent with the stand-alone results discussed above. We also find that the association between R&D and analyst coverage decreases with scale effects of R&D, consistent with stand-alone results. However, we find that the impact of investors' attention on analyst coverage for R&D firms is either marginally significant or insignificant in the combined analysis. These findings suggest that the impact of cross-sectional determinants are not subsumed by the presence of other cross-sectional determinants (except investors' attention), indicating that the cross-sectional determinants considered in this study are independent from each other.

This paper contributes to several streams of extant research. Our study contributes to the literature that investigates the relationship between analyst coverage and R&D. Barth et al. (2001) document a positive association between R&D and analyst coverage. However, they do not investigate what particular attribute of R&D leads to this positive association. In this paper we complement Barth et al. (2001) in two ways. First, we identify cross-sectional determinants of the relationship between R&D and analyst coverage such as reporting biases, uncertainty associated with R&D, investors' attention and scale effect of R&D. Second, we identify which particular cross-sectional determinant explains the positive relationship between R&D and analyst coverage documented by Barth et al. (2001).

Our paper further contributes to the prior literature about the negative consequences of immediate expensing of R&D (Lev and Zarowin 1999; Lev 2001; Lev et al. 2005). Several researchers argue that the immediate expensing of R&D negatively affects the informativeness or usefulness of financial statements for equity investors because it biases accounting numbers (Amir and Lev 1996; Lev and Zarowin 1999; Lev et al. 2005). While prior research primarily focuses on the demand for accounting information (i.e., the usefulness or informativeness of accounting information for equity investors), we complement prior research by providing evidence on the supply of information by financial analysts (i.e., analyst coverage). Our evidence suggests that reporting biases resulting from expensing of R&D negatively affect not only the demand for information by equity investors, but also the supply of information by financial analysts. Prior research suggests that financial analysts are likely to fill the information gap (lack of informativeness) in financial statements resulting from expensing of R&D (Barth et al. 2001; Kimbrough 2007). However, our evidence suggests that financial analysts themselves are negatively affected by reporting biases. Consequently, they are less likely to fill the information gap in the financial statements arising from expensing of R&D. Therefore, our findings suggest that the negative consequences of expensing of R&D could be more severe than that suggested in the prior literature (Amir and Lev 1996; Lev and Zarowin 1999; Lev et al. 2005). The International Financial Reporting System (IFRS) requires the capitalization of development costs for internally developed intangibles such as R&D (International Accounting Standard 38). Given that the U.S. is on the path to converge to IFRS, our findings about the impact of reporting biases of expensing of R&D on analyst coverage for R&D firms could be useful to standard setters in evaluating the consequences of expensing of R&D as compared to capitalization of R&D.

This paper also contributes to the ongoing discussion about the scale effects of R&D. Prior research documents scale the effects of R&D impact productivity, future earnings, stock returns and number of patents generated from R&D investments (Cohen and Klepper 1996; Henderson and Cockburn 1996; Ciftci and Cready 2011). We extend the prior literature by documenting that the scale effects of R&D also affect analyst coverage for R&D firms.

This paper also enriches the existing literature that investigates the implications of uncertainty associated with R&D. Prior research suggests that uncertainty associated with R&D affects numerous attributes of R&D firms such as stock market and bond market valuations, information asymmetry and insider gains, value of analyst recommendations and stock return volatility (Aboody and Lev 2000; Chan et al. 2001; Shi 2003; Palmon and Yezegel 2012).[1] We contribute to this stream of research by documenting the fact that the uncertainty associated with R&D also affects analyst coverage for R&D firms. Finally, while prior research focuses primarily on the impact of investor attention on stock market valuation of R&D firms (Owen 2002), this paper complements this literature by documenting the impact of investor attention on analyst coverage for R&D firms.

The rest of the paper is organized as follows. Section 2 outlines the relevant literature and hypotheses. Section 3 briefly discuss the U.S. adoption of IFRS through the lens of its implications for R&D. Section 4 introduces the research design and provides the sample selection, descriptive statistics and Pearson correlations. Section 5 reports the empirical results, and Section 6 concludes the paper.

2. Literature Review and Hypotheses

2.1. Analyst Coverage and the Informativeness of the Firm's Disclosures

Prior research suggests that business enterprises with better information environment and more precise public disclosures could attract greater analyst following because better disclosures may reduce analysts' information acquisition costs (Beyer et al. 2010). Lang and Lundholm (1993) argue that firms' voluntary disclosures reduce analysts' information acquisition costs and increase analyst following. They find that firms with more informative disclosures have greater analyst following, less dispersion in analyst forecast and less volatility in forecast revisions. Healy et al. (1999) show that firms with increased analyst ratings of disclosure experience an increase in their analyst following. Francis et al. (1997) document an increase in analyst following for firms making conference calls. In a similar vein, Lang and Lundholm (1996) document a positive association between analyst following and ratings of firms' disclosures available in the Report of the Financial Analyst Federation Corporation Information Committee (AIMR rankings).

However, several studies also suggest that a better information environment and more precise public information are associated with less demand for analyst services (Beyer et al. 2010). Fischer and Stocken (2010) show that analysts stop following a firm when the public information is sufficiently precise. Diamond (1985) suggests that firm-provided disclosures reduce the benefits of following a firm, thereby reducing private incentives to collect more information. Additionally, Zhang and Toffanin (2018) argue that analysts have more incentives to follow firms with higher R&D investments, to discover mispricing opportunities. These arguments suggest that analysts are likely to follow firms whose public disclosures are less precise, because less precise disclosures could make analysts' forecasts and recommendations more valuable to investors. Specifically, a reason for the poor information environment that could incentivize analysts to acquire information about R&D firms is the proprietary nature of R&D information (Bloom et al. 2013; Boone et al. 2016). R&D investments are linked to higher information asymmetry and are, therefore, harder to value by investors (Lev and Sougiannis 1996; Chan et al. 2001; Canace et al. 2023). This information asymmetry is exacerbated by managers' reluctance to share in-depth information about their R&D investments to the public, in order to maintain their competitive advantage (Bhattacharya and Ritter 1980; Cohen et al. 2000; Canace et al. 2023). Consequently, through their role as information intermediaries, analysts play a crucial role in incorporating private information about R&D investments into stock prices without disclosing such proprietary information (Canace et al. 2023). Consistent with this argument, Kirk (2011) finds that high-R&D investment firms have a higher tendency to interact with analysts in order to decrease uncertainty about their firm's earnings. Similarly, Green et al. (2014) document the fact that high-R&D firms have a higher propensity to attend broker-hosted conferences in order to attract more analyst coverage and attention. Moreover, Bellstam et al. (2021) share a section of an analyst report from May 1993 which elaborates on the important role of Walmart's innovative investments on its competitive advantage without providing any proprietary information.

Overall, the prior literature provides conflicting arguments about the impact of informativeness of firms' disclosures on analyst coverage. While one stream of research suggests that more informative disclosures attract financial analysts (Lang and Lundholm 1993, 1996; Healy et al. 1999), another stream of research suggests that precision of public information decreases the investors' demand for analyst services (Diamond 1985; Fischer and Stocken 2010).

2.2. Accounting Treatment of R&D and Reporting Biases

Lev and Sougiannis (1996) document the fact that R&D is positively associated with future earnings, indicating that, similar to other assets, R&D has future economic benefits. However, U.S. GAAP requires that R&D expenditures be immediately expensed, while it permits the capitalization of tangible investments such as plant, property, and equipment. Darrough and Ye (2007) suggest that expensing the entire amount of R&D expenditures can lead to an understated book value of both assets and current earnings.[2] Consistent with these arguments, prior research suggests that expensing of R&D is a form of conservative accounting, which is referred to as ex ante (Pope and Walker 1999), and unconditional (Beaver and Ryan 2005; Ryan 2006). Expensing of R&D is heavily criticized by several studies (Amir and Lev 1996; Lev and Zarowin 1999; Lev 2001, 2004). Lev and Zarowin (1999) suggest that expensing of R&D severely distorts the matching principal in accounting, adversely affecting the informativeness of accounting information.[3] Lev (2001) suggests that "expensing intangibles leads to biased and deficient reporting of firms' performance and value" (p. 7).

While some studies describe expensing of R&D as a conservative accounting policy (Pope and Walker 1999; Beaver and Ryan 2005; Ryan 2006), Lev et al. (2005) argue that no accounting principle consistently applied can be conservative through the firm's entire life. They suggest that if earnings under a conservative accounting rule are understated during certain periods, they have to be overstated in other periods. They argue that firms with a high R&D growth rate relative to their profitability report conservatively, while firms with a low R&D growth rate report aggressively. Moreover, they document that investors fixate on the reported profitability without considering R&D growth. Specifically, they find that conservatively reporting firms are undervalued, while aggressively reporting firms are overvalued. Similarly, Penman and Zhang (2002) suggest that expensing of R&D reduces current earnings by creating hidden reserves when a firm is increasing its R&D investment. In a similar vein of research, Khallaf and Kannan (2024) find a significant increase in the likelihood of management earnings forecasting issuances for firms with higher unrecognized intangibles with greater earnings uncertainty. However, management can release these hidden reserves in subsequent periods and increase earnings by decreasing R&D investment (Penman and Zhang 2002). In the same vein, Lev and Zarowin (1999) suggest that if the rate of R&D spending is constant over time, earnings will be the same whether R&D is capitalized or immediately expensed. They further suggest that it is only when investment in R&D changes over time that "earnings based on immediate expensing will differ materially from economic earnings based on capitalization of intangibles" (p. 372). They also argue that expensing of R&D will reduce the informativeness of earnings only when firms increase their investments in R&D. Overall, while early studies argue that expensing of R&D is a conservative accounting policy, subsequent studies suggest that the impact of expensing of R&D on accounting numbers could be conservative as well as aggressive, depending on R&D growth.[4]

2.3. Reporting Biases Resulting from Expensing of R&D and Analyst Coverage

As discussed above, prior research suggests that, due to reporting biases resulting from expensing of R&D, financial statements are less informative for R&D firms (Amir and Lev 1996; Lev and Zarowin 1999). Kimbrough (2007) suggests that analysts' acquisitions of private information for R&D companies could reduce the information gap (lack of informativeness) in financial statements caused by expensing of R&D. Consequently, analysts could benefit more from private information acquisition by filling the information gap in the financial statements caused by reporting biases arising from expensing of R&D, and this, in turn, may increase analyst coverage for R&D firms. Moreover, mandatory disclosures of R&D expenditures have shown to significantly impact analyst forecasts, as observed by recent studies focusing on pharmaceutical sectors in emerging markets (Xu et al. 2021). However, reporting biases resulting from expensing of R&D might also have an opposite effect on analyst coverage for R&D firms. Lang and Lundholm (1996) suggest that analyst coverage is greater (smaller) for firms with more (less) informative disclosures, because information acquisition costs are smaller (greater) for firms with more (less) informative disclosures. Mandatory disclosures of R&D expenditures have a significant impact on the informativeness of financial statements and, consequently, on analyst forecasts. Xin et al. (2024) demonstrated that such disclosures reduce information asymmetry and enhance forecast accuracy. Given that reporting biases are likely to reduce the informativeness of the financial statements (Lev and Zarowin 1999), they might increase analysts' information acquisition costs and therefore decrease analysts' willingness to follow R&D firms. Consequently, there are competing hypotheses about the impact of reporting biases on analyst coverage for R&D firms. Therefore, we cannot, a priori, determine the impact of reporting biases on analyst coverage for R&D firms. Thus, we state the following null hypothesis.

H1. *Reporting biases resulting from expensing of R&D compared to capitalization of R&D do not have any effect on the relationship between R&D and analyst coverage.*

2.4. Uncertainty Associated with R&D and Analyst Coverage

Lev (2001) suggests that innovation activity is highly risky relative to other corporate activities such as production, marketing, and finance, and that riskiness of intangibles is substantially higher than that for physical, and even financial, assets. Scherer et al. (2001) suggest that the top 10 percent of patents (in Germany and U.S.) accounted for 81–93% of total patent value, implying that the majority of patents were essentially worthless and that investment in those patents is a total loss. Lev (2001) suggests that the innovation process is highly skewed: few products or processes are blockbusters, while the rest are duds. In addition, he suggests that the prospect of a total loss is common to many innovative activities such as drug development; however, even highly risky physical projects such as commercial property rarely end up with a total loss. Chan et al. (2001) suggest that R&D-intensive firms' prospects are tied to the success of new, untested technologies and hence are highly unpredictable. Consistent with the greater uncertainty associated with R&D, they document the fact that volatility of stock returns is positively associated with R&D. Barron et al. (2002) suggest that analysts' uncertainty increases and analysts' consensus decreases with the level of a firm's intangible assets. Boone and Raman (2001) document the fact that the adverse selection component of spread is higher for R&D-intensive firms than that for non-R&D-intensive firms. Uncertainty related to R&D investments remains a significant factor affecting analyst coverage. The recent analysis by Widianingsih et al. (2023) indicates that higher R&D intensity correlates with increased risk and volatility in firm performance, further influencing the demand for analyst coverage. Overall, prior research suggests that the uncertainty associated with R&D is much greater than that for other investments. In fact, the uncertainty associated with R&D is the primary reason that the FASB requires expensing of R&D in the US (Kothari et al. 2002).[5]

Greater uncertainty associated with R&D might increase investors' demand for analyst forecasts for R&D firms. Consistent with this argument, Palmon and Yezegel (2012) document the fact that analysts' stock recommendations are more valuable for R&D firms, suggesting that investors have greater demand for information for R&D firms. The relationship between R&D intensity and management forecast accuracy has been further elucidated in recent studies. Kannan et al. (2023) found that higher R&D intensity is associated with increased conservatism in management forecasts, which in turn affects analyst coverage. The increased investor demand for analyst forecasts could create opportunities for private information acquisition for analysts and therefore increase analyst coverage for R&D firms. However, greater uncertainty associated with R&D might have an opposite effect on analyst coverage for R&D firms. Weiss (2010) documents the fact that stickiness in costs increases analysts' earnings-forecast errors which, in turn, decreases analyst coverage. Gu and Wang (2005) find a positive association between analysts' forecast errors and a firm's R&D intensity, suggesting that greater uncertainty associated with R&D increases analyst forecast errors. Therefore, the greater the analyst forecast errors caused by greater uncertainty associated with R&D, the lower the analyst coverage for R&D firms. Consequently, there are competing hypotheses about the impact of uncertainty on the relationship between R&D and analyst coverage. Therefore, we do not have, a priori, a clear prediction about the impact of uncertainty on analyst coverage for R&D firms. Hence, we state the following null hypothesis.

H2. *The uncertainty associated with R&D has no effect on the relationship between R&D and analyst coverage.*

2.5. Investor Attention and Analyst Coverage

Owen (2002) suggests that high-technology shares were increasingly popular through the late 1990s. He also claims that once investors become interested in one particular type of company an element of herd behavior arises, as investors are influenced by the actions of others, and an informational cascade develops. He argues that some individuals are over-confident, whilst others copy the actions of previous investors. He further suggests that this pattern of behavior was not limited to just the American markets, as it was repeated worldwide with markets such as the Alternative Investment Market (AIM) in the UK, the Neuer Market in Germany, the New Capital Market in New Zealand and the Nouveau Marche in France, which all outperformed the main Stock Exchange boards in their respective countries. As a result of these irrational behaviors, high-technology stocks receive substantial attention.

If high-technology stocks receive substantial investors' attention, this could also affect analyst coverage. Financial analysts are employed by investment banks whose profit depend on trade commissions generated from stock trades. Consequently, financial analysts follow the firms that will increase their employer's trading commissions. Consistent with this argument, Beyer et al. (2010) suggest that analysts have incentives to maximize the trading volume in the stocks they cover. When R&D-intensive high-technology stocks receive greater investors' attention, financial analysts will start following these firms to increase trade commissions for their employer. Consequently, investor attention is likely to increase analyst coverage for R&D firms. Therefore, we state the following hypothesis in an alternative form, as follows:

H3. *The relationship between analyst coverage and R&D increases with investors' attention.*

2.6. Scale Effects of R&D and Analyst Coverage

Schumpeter (1942) suggests that larger firms are more productive than smaller firms in implementing and successfully exploiting R&D efforts. Henderson and Cockburn (1996) suggest that in principle, size confers several advantages in performing R&D. First, in the absence of fully functioning markets for innovation, larger firms may be able to spread the fixed costs of research over a larger sales base. Second, larger firms may be able to exploit economies of scale and scope in the conduct of research itself. Consistent with these arguments Henderson and Cockburn (1996) document the fact that larger research efforts are more productive, not only because they enjoy economies of scale, but also because they realize economies of scope by sustaining diverse portfolios of research projects that capture internal- and external-knowledge spillovers. In addition, Cohen and Klepper (1996) suggest that the larger the firm, the greater the output to which it can apply the fruits of its R&D, and hence the higher its returns from R&D. Alternatively, the larger the firm, the greater the level of output over which it can average the costs of R&D. Consistent with these arguments, Ciftci and Cready (2011) document the fact that larger firms generate higher future earnings from R&D than smaller firms.

Hayes (1998) suggests that analysts' incentives to initiate coverage are strongest for stocks they expect to perform well. Therefore, if larger firms are more productive and generate higher earnings from R&D than smaller firms, financial analysts are more likely to cover larger R&D firms. Consequently, we expect scale effects of R&D to increase analyst coverage for R&D firms. Therefore, we state the following hypothesis in an alternative form:

H4. *The relationship between analyst coverage and R&D increases with scale effects of R&D.*

3. The U.S. Adoption of IFRS

Although the US has not fully adopted International Financial Reporting Standards (IFRS) for financial reporting, the U.S. Financial Accounting Standards Board (FASB) and the International Accounting Standards Board (IASB) have been working on a project to converge certain aspects of U.S. Generally Accepted Accounting Principles (GAAP) and the IFRS to enhance the comparability of financial reporting globally. The purpose of the convergence efforts is to reduce differences between the GAAP and IFRS, to create a more consistent and globally accepted financial reporting framework. The adoption of the IFRS in the U.S. was a topic interest for SEC Chairs with differing degrees of success, particularly from 2005 to 2017 (Becker et al. 2023). This period witnessed attempts to use the SEC's regulatory framework to advance IFRS adoption. These efforts still faced challenges. Some of these key challenges are due to the US legal and regulatory framework, cost of implementation, stakeholders' resistance, and other political conditions.

The SEC chair, Christopher Cox, emerged as a critical advocate for global accounting standards during this time (Black et al. 2011). Cox advocated for enhanced investor trust and market comparability by creating one high-quality, comprehensive, and rigorously applied global standards system that would support investment decision-making while decreasing compliance costs for issuers. Political events both inside and outside the SEC showed that opportunities for policy changes can close unexpectedly fast. Financial disruptions in particular are a big problem that slow down the adoption process and highlight how regulatory plans can be at risk when faced with larger economic problems (Newman 2013). An integrated methodology would streamline financial reporting and decrease economic burden, ultimately benefitting shareholders with lower reporting costs (Becker et al. 2023).

The ongoing debate over whether R&D costs should be expensed or capitalized has caught the attention of SEC chairs. Christopher Cox gained widespread recognition for his innovative approach to treating R&D expenses under IFRS adoption in the US, including taking proactive steps even before official guidelines had been issued for foreign entities—prompting more universal accounting norms across US firms. His support of IFRS for the treatment of R&D expenditures stands out, especially regarding capitalization under certain conditions. This practice would improve relevance and usefulness significantly, providing investors and stakeholders with more relevant financial data that aid decision-making where firms have made investments in future growth (Becker et al. 2023).

The real questions for those who adopt these standards become whether they understand the implications of these changes in financial reporting and analysis and how these changes will enhance transparency and comparability. As the U.S. moves toward adopting IFRS, the debate over R&D accounting treatment resurfaces as a significant potential challenge, emphasizing the significance of strategic thinking and international collaboration in achieving the goal of enhancing financial reporting comparability and a unifying set of global accounting standards. Even though there are variations in the financial reporting environment (US-GAAP and IFRS) including governance, legal regime, audit practices, and securities regulations, the SEC should not postpone actions until all elements of the financial reporting environment are globally harmonized (Alon and Dwyer 2016).

4. Research Design

We investigate the relationship between R&D intensity and analyst coverage using the following pooled cross-sectional ordinary least squares (OLS) regression:

$$\begin{aligned}\text{COVRGE}_{it} = {} & \beta_0 + \beta_1\text{RND}_{it} + \beta_2\text{UNCRTNY}_{it} + \beta_3\text{ADV}_{it} + \beta_4\text{DEPR}_{it} + \beta_5\text{INTANA}_{it} + \beta_6\text{GDWLA}_{it} + \beta_7\text{LMV}_{it} \\ & + \beta_8\text{DISSUE}_{it} + \beta_9\text{GROWTH}_{it} + \beta_{10}\text{VOLUME}_{it} + \beta_{11}\text{RET}_{it} + \beta_{12}\text{absEARN}_{it} + \beta_{13}\text{ROA}_{it} + \beta_{14}\text{LOSS}_{it} + \varepsilon_{it}\end{aligned} \quad (1)$$

The definitions of the variables in Equation (1) are provided in Table 1. We include year and industry indicator variables in all estimations to control for year and industry fixed effects. Industry indicator variables are based on the Fama and French (1997) 48 industry definitions. Instead of including industry fixed effects, Barth et al. (2001) use industry-adjusted measures of R&D and other intangibles. We prefer to use industry fixed effects rather than industry-adjusted measures because industry-adjusted measures produce both positive and negative values which may not be possible to interpret when we interact industry-adjusted R&D with log of firm size. For example, when we interact industry-adjusted R&D with log of market value (LMV), both variables will have positive and negative values. Consequently, interpretation of the interaction term will not be possible. In addition, we cluster firm-year observations by firm to eliminate autocorrelation, as suggested by Petersen (2009). To alleviate the influence of outliers, we winsorize all continuous variables (COVRGE, RND, ADV, DEPR, INTANA, GDWAL, LMV, GROWTH, VOLUME, STDRET, ROA, STDROA) except RET at the top and bottom 1% of respective annual distributions. Absolute change in earnings (absEARN) is winsorized at the top and bottom 1% of signed change in earnings before taking the absolute value.

Table 1. Definitions of Variables.

COVRGE	=Number of analysts issuing one-year-ahead EPS forecasts for year *t* earnings. Number of analysts is generated from I/B/E/S.
RDG_ROE	=The difference between {RDG/[(RDG/2) + 1]} and ROE. RDG is annualized R&D growth calculated as $[(RD_t - RD_{t-4})/RD_{t-4}]/4$ where RD_t is R&D expenditures (XRD from Compustat) in year *t*. ROE is net income (NI from Compustat) in year *t* divided by average book value of equity (CEQ from Compustat) over years *t* and $t-1$. We delete firm-year observations with negative value of average book value of equity.
DIFROA	=Difference in earnings between capitalization and expensing of R&D. It is calculated as R&D expense (XRD from Compustat) minus amortization expense divided by total assets (AT from Compustat). Amortization expense is calculated based on 20% amortization rate over years, from $t-1$ to $t-5$ (Chan et al. 2001; Lev et al. 2005).
AGRSV	=An indicator variable which equals one if the firm is an aggressive firm, and 0 otherwise. Aggressive firms are those in the bottom 25% of reporting bias (i.e., RDG_ROE or DIFROA).
CONSRV	=An indicator variable which equals one if the firm is an conservative firm, and 0 otherwise. Conservative firms are those in the top 25% of reporting bias (i.e., RDG_ROE or DIFROA).
RND	=R&D expense (XRD from Compustat) divided by operating expense. Operating expense is calculated as sales revenue (SALE from Compustat) minus operating income (OIADP from Compustat).
UNCRTNY	=The measure of uncertainty. It is either STDROA or STDRET, as defined below.
STDROA	=Standard deviation of ROA over five years, from *t* to $t-4$. ROA is calculated as income before extraordinary items (IB from Compustat) divided by total assets (AT from Compustat).
STDRET	=Standard deviation of monthly stock returns over the twelve months in fiscal year *t*.
ADV	=Advertising expense (XAD from Compustat) divided by operating expense. If XAD is negative or is missing, it is set to 0.
DEPR	=Depreciation expense (DP from Compustat) divided by operating expense. If DP is negative or missing, it is set to 0.
INTANA	=Intangible assets (INTAN from Compustat) divided by total assets. If INTAN is negative or missing, it is set to 0.
GDWLA	=Goodwill (GDWL from Compustat) divided by total assets. If GDWL is missing, it is set to 0.
LMV	=Log of market value of equity at the end of the year *t*. Market value of equity is calculated as share price (PRCC_F from Compustat) times the shares outstanding (CSHO from Compustat).
DISSUE	=An indicator variable which equals 1 if a firm issued debt (DLTIS from Compustat) or equity (SSTK from Compustat) in years $t-1$, or *t*, or $t+1$, and 0 otherwise.
GROWTHS	=Sales growth calculated as $(SALE_{t-1}/SALE_{t-3})^{1/3}$. SALE is sales revenue (SALE from Compustat).
VOLUMTE	=Trading volume (CSHTR_F from Compustat) in millions of shares in year *t*.

Table 1. *Cont.*

RET	=Market-adjusted buy-and-hold stock returns over the twelve months in year *t*. Market-adjusted returns are calculated as a firm's monthly stock return minus the value-weighted monthly market return (VWRETD from CRSP). Monthly stock returns are generated from CRSP Monthly Files.
absEARN	=Absolute value of change in earnings in year *t*. Change in earnings are calculated as change in income before extraordinary items (IB from Compustat) in year *t* minus that in year $t-1$ divided by total assets (AT from Compustat) in year $t-1$.
ROA	=Income before extraordinary items (IB from Compustat) divided by total assets (AT from Compustat).
LOSS	=An indicator variable which equals 1 if income before extraordinary items (IB from Compustat) is negative, and 0 otherwise.

We deflate RND, ADV, and DEPR with operating expenses following Barth et al. (2001). RND in Equation (1) shows the association between R&D and analyst coverage. Barth et al. (2001) documents the fact that R&D is positively associated with analyst coverage. Therefore, we expect the coefficient estimate of RND in Equation (1) to be positive. UNCRTNY in Equation (1) shows the association between uncertainty and R&D. We have two measures of uncertainty: STDROA and STDRET. The two measures of uncertainty associated with R&D are used to examine the impact of uncertainty on analyst coverage for R&D firms. Following Barth et al. (2001), we include ADV, DEPR, INTANA, GDWLA, LMV, VOLUME and GROWTH in our model. We also add RET, absEARN and ROA into our model, following Healy et al. (1999). Consistent with Amir et al. (2003), we add LOSS into our model.

In addition to the relationship between analyst coverage and R&D, Barth et al. (2001) also investigate the relationship between analyst effort and R&D. We do not investigate the relationship between R&D and analyst effort, for several reasons. The decision to omit measures of analysts' effort is motivated by the following key considerations. First, analyst coverage represents an ex ante decision made in anticipation of factors like intangible assets. In contrast, measures of analysts' effort, such as the average number of firms covered (Barth et al. 2001) or analysts' forecast accuracy (Harford et al. 2019), are ex post outcomes influenced by the decision to cover a firm, and both represent actual rather than expected measures of analysts' efforts. By focusing on analyst coverage, we aim to capture the intrinsic motivation that precedes analysts' decisions. Second, measures of analysts' effort (e.g., analysts' forecast accuracy) are inherently subjective and may be influenced by various factors beyond the incentive to cover a firm, such as analysts' experience and knowledge. This subjectivity introduces complexity and potential confounding factors to the study. Third, Shon and Young (2011) explore factors influencing an analyst's choice to drop coverage. Their findings, highlighting the impact of economic incentives like analyst compensation and attracting business for the brokerage house on the decision to discontinue coverage, align with our decision to exclude analyst effort. Finally, our study is specifically designed to explore the cross-sectional determinants of the association between R&D and analyst incentives to cover a firm. Excluding measures of analysts' effort allows us to focus on the primary determinants of analyst coverage (reporting biases, uncertainty, investor attention, and scale effects), aligning with our research objectives.

Furthermore, it is worth noting that in previous research, uncertainty, one of the determinants of analyst coverage in our paper, has been gauged using analyst forecast errors (Gu and Wang 2005; Weiss 2010). For example, Gu and Wang (2005) argue that greater uncertainty was related to R&D results in terms of increased analyst forecast errors. Additionally, Barron et al. (2002) document the fact that analyst consensus tends to decrease with the level of a firm's intangible assets. In a similar vein, the accuracy of analyst forecast errors has also been utilized in other studies to measure analysts' effort (Harford et al. 2019). Therefore, we posit that uncertainty may capture, in part, the analysts' effort in our study.

To test for H1, we use two proxies of reporting bias from expensing of R&D compared to capitalization of R&D. Consistent with Lev et al. (2005), the first proxy is based on the difference between return on equity (ROE) and annualized R&D growth (RDG). We develop our second measure, DIFROA, based on the difference in earnings in the cases of capitalization and expensing of R&D. When a firm's R&D is growing over time, earnings under capitalization of R&D will be much greater than those under expensing of R&D. Consequently, DIFROA will be positive, indicating that expensing of R&D understates earning compared to capitalization of R&D (i.e., expensing of R&D leads to conservative reporting). However, when a firm's R&D is decreasing over time, earnings under capitalization of R&D will be smaller than those under expensing of R&D. Therefore, DIFROA will be negative, indicating that expensing of R&D overstates earnings (expensing of R&D leads to aggressive reporting). We separate firm-year observations into three categories based on reporting biases resulting from expensing of R&D: aggressive (conservative) firms are those in the bottom (top) 25% of measures of reporting bias (RDG_ROE and DIFROA) and neutral firms are those between 25% and 75% of measures of reporting bias. We estimate the following equation to test H1:

$$\begin{aligned} \text{COVRGE}_{it} = {} & \beta_0 + \beta_1\text{AGRSV}_{it} + \beta_2\text{CONSRV}_{it} + \beta_3\text{RND}_{it} + \beta_4\text{UNCRTNY}_{it} + \beta_5\text{ADV}_{it} + \beta_6\text{DEPR}_{it} \\ & + \beta_7\text{INTANA}_{it} + \beta_8\text{GDWLA}_{it} + \beta_9\text{LMV}_{it} + \beta_{10}\text{DISSUE}_{it} + \beta_{11}\text{GROWTH}_{it} + \beta_{12}\text{VOLUME}_{it} + \beta_{13}\text{RET}_{it} \\ & + \beta_{14}\text{absEARN}_{it} + \beta_{15}\text{ROA}_{it} + \beta_{16}\text{LOSS}_{it} + \beta_{17}\text{RND}_{it} \times \text{AGRSV}_{it} + \beta_{18}\text{RND}_{it} \times \text{CONSRV}_{it} + \varepsilon_{it} \end{aligned} \tag{2a}$$

The only difference between Equations (1) and (2a) is that we add CONSRV and AGRSV into our model and interact them with RND in Equation (2a). Our variables of interest are RND and its interactions with CONSRV and AGRSV. The coefficient estimate of RND in Equation (2a) shows the association between R&D and analyst coverage for neutral firms. The coefficient estimate of RND×CONSRV (RND×AGRSV) shows the difference in the coefficient estimate of RND between neutral and conservative (aggressive) firms. If the association between R&D and analyst coverage is lower (higher) for conservative firms than that for neutral firms, then the coefficient estimate of RND×CONSRV should be negative (positive). H1 predicts that reporting biases from expensing of R&D compared to capitalization do not affect analyst coverage for R&D firms. Therefore, H1 predicts that there is no significant difference between neutral firms and conservative (or aggressive) firms in the association between R&D and analyst coverage. Thus, H1 anticipates that both interaction terms, RND×CONSRV and RND×AGRSV, should be insignificant. To test H2, we estimate the following equation:

$$\begin{aligned} \text{COVRGE}_{it} = {} & \beta_0 + \beta_1\text{RND}_{it} + \beta_2\text{UNCRTNY}_{it} + \beta_3\text{ADV}_{it} + \beta_4\text{DEPR}_{it} + \beta_5\text{INTANA}_{it} + \beta_6\text{GDWLA}_{it} \\ & + \beta_7\text{LMV}_{it} + \beta_8\text{DISSUE}_{it} + \beta_9\text{GROWTH}_{it} + \beta_{10}\text{VOLUME}_{it} + \beta_{11}\text{RET}_{it} + \beta_{12}\text{absEARN}_{it} + \beta_{13}\text{ROA}_{it} \\ & + \beta_{14}\text{LOSS}_{it} + \beta_{15}\text{RND}_{it} \times \text{UNCRTNY}_{it} + \varepsilon_{it} \end{aligned} \tag{2b}$$

The only difference between Equations (1) and (2b) is that we interact UNCRTNY with RND in Equation (2b). H2 predicts that uncertainty does not affect the association between analyst coverage and R&D. Therefore, the interaction term, RND×UNCRTNY, in Equation (2b), is expected to be insignificant. To test H3, we estimate the following equation:

$$\begin{aligned} \text{COVRGE}_{it} = {} & \beta_0 + \beta_1\text{RND}_{it} + \beta_2\text{UNCRTNY}_{it} + \beta_3\text{ADV}_{it} + \beta_4\text{DEPR}_{it} + \beta_5\text{INTANA}_{it} + \beta_6\text{GDWLA}_{it} \\ & + \beta_7\text{LMV}_{it} + \beta_8\text{DISSUE}_{it} + \beta_9\text{GROWTH}_{it} + \beta_{10}\text{VOLUME}_{it} + \beta_{11}\text{RET}_{it} + \beta_{12}\text{absEARN}_{it} + \beta_{13}\text{ROA}_{it} \\ & + \beta_{14}\text{LOSS}_{it} + \beta_{15}\text{RND}_{it} \times \text{VOLUME}_{it} + \varepsilon_{it} \end{aligned} \tag{2c}$$

Following Barber and Odean (2008) and Hou et al. (2009), we use trading volume (VOLUME) as a proxy for investors' attention. To test H3, we interact VOLUME with RND in Equation (2c). H3 predicts that the association between R&D and analyst coverage increases with investor attention. Therefore, the interaction term RND×VOLUME is expected to be positive. To test H4, we estimate the following equation:

$$\begin{aligned} \text{COVRGE}_{it} = {} & \beta_0 + \beta_1\text{RND}_{it} + \beta_2\text{UNCRTNY}_{it} + \beta_3\text{ADV}_{it} + \beta_4\text{DEPR}_{it} + \beta_5\text{INTANA}_{it} + \beta_6\text{GDWLA}_{it} \\ & + \beta_7\text{LMV}_{it} + \beta_8\text{DISSUE}_{it} + \beta_9\text{GROWTH}_{it} + \beta_{10}\text{VOLUME}_{it} + \beta_{11}\text{RET}_{it} + \beta_{12}\text{absEARN}_{it} + \beta_{13}\text{ROA}_{it} \\ & + \beta_{14}\text{LOSS}_{it} + \beta_{15}\text{RND}_{it} \times \text{LMV}_{it} + \varepsilon_{it} \end{aligned} \tag{2d}$$

To measure scale effects of R&D on analyst coverage, we use log of firm size (LMV), consistent with the prior literature (Cohen and Klepper 1996; Henderson and Cockburn 1996; Ciftci and Cready 2011). If R&D has scale effects on analyst coverage, the association between R&D and analyst coverage should be greater for large firms than for small firms. To test the impact of scale effects of R&D on the association between R&D and analyst coverage, we interact RND with LMV in Equation (2d). If the association between analyst coverage and R&D is increasing with scale effects of R&D, as predicted by H4, then the interaction term, RND×LMV, should be positive.

4.1. Sample Selection

We include all the firm-year observations in CRSP, Compustat and I/B/E/S that have data for estimation of Equation (1) with non-missing value of RDG_ROE. Calculation of RDG_ROE requires R&D data over the past five years (i.e., from years t to $t-4$). Therefore, we require the firm-year observations to have s positive value of R&D over the past five years. We also delete firm-year observations with a negative average book value of equity (averaged over years t to $t-1$), because average book value of equity is used in the calculation of RDG_ROE. In addition, we require the firm-year observations to have sales revenue of at least USD 1 million. Following Barth et al. (2001), we exclude financial industries (4-digit SIC = 6000–6999) and utilities (4-digit SIC = 4900–4999). Our sample period is from 1985 to 2018. We generate financial statement data from Compustat Annual Files. Analyst coverage is generated from I/B/E/S. Stock returns are generated from CRSP Monthly Files. There are 29,203 firm-year observations in our sample when we use RDG_ROE as the measure of reporting bias and 27,242 firm-year observations when we use DIFROA as the measure of reporting bias. Calculation of DIFROA requires the data availability for R&D over the past six years (from years t to $t-5$). Therefore, the sample size with DIFROA is slightly smaller than that for RDG_ROE.

4.2. Descriptive Statistics and Pearson Correlations

Table 2 presents the descriptive statistics. The mean and median values of analyst coverage (COVRGE) are 10.37 and 7.00, respectively. Our first measure of reporting bias, RDG_ROE (Lev et al. 2005), is based on the difference between ROE and annualized R&D growth. Lev et al. (2005) separate firm-year observations into aggressive, neutral and conservative firms, using RDG_ROE. To prove that their measure captures reporting biases from expensing of R&D, Lev et al. (2005) document the fact that for firms that report aggressively, ROE under capitalization of R&D is smaller than that under expensing of R&D. However, for firms that report conservatively, they document the opposite relation (i.e., ROE under capitalization of R&D is greater than that under expensing of R&D). Based on these results, they conclude that RDG_ROE captures the reporting biases arising from expensing of R&D compared to capitalization of R&D. We develop our second measure of reporting bias, DIFROA, which is based on the difference in earnings in the cases of capitalization and expensing of R&D. DIFROA is designed to capture the reporting bias resulting from expensing of R&D compared to that when R&D is capitalized. When a firm's R&D is growing (decreasing) over time, earnings under capitalization of R&D will be greater (smaller) than earnings under expensing of R&D. Therefore, DIFROA will be positive (negative). Hence, when R&D is growing (decreasing) over time, a firm is likely to report conservatively (aggressively).

The mean and median values of RDG_ROE are positive: 0.1732 and 0.0468, respectively, in Table 2. Similarly, the mean and median values for DIFROA are positive: 0.0154 and 0.0071, respectively. These results suggest that, on average, expensing of R&D leads to conservative reporting compared to capitalization of R&D (because RDG_ROE and DIFROA are positive, on average). That is, on average, earnings under capitalization of R&D are greater than those under expensing of R&D, suggesting that expensing of R&D, on average, understates earnings compared to capitalization of R&D. Therefore, the descriptive statistics indicate that expensing of R&D, on average, leads to more conservative reporting compared to capitalization of R&D.

Table 2. Descriptive Statistics.

	MEAN	STD	Q1	MEDIAN	Q3
COVRGE	10.3727	9.7232	3.0000	7.0000	14.0000
RDG_ROE	0.1732	0.5071	−0.0992	0.0468	0.3058
DIFROA	0.0154	0.0453	0.0003	0.0071	0.0260
RND	0.1156	0.1442	0.0212	0.0661	0.1586
STDROA	0.0771	0.1087	0.0192	0.0393	0.0885
STDRET	0.1260	0.0732	0.0757	0.1089	0.1554
ADV	0.0111	0.0278	0.0000	0.0000	0.0088
DEPR	0.0562	0.0403	0.0312	0.0460	0.0682
INTANA	0.1317	0.1662	0.0000	0.0605	0.2070
GDWLA	0.0876	0.1256	0.0000	0.0192	0.1389
LMV	6.4501	2.0858	4.9399	6.2918	7.8033
DISSUE	0.7799	0.4143	1.0000	1.0000	1.0000
GROWTH	0.0955	0.1645	0.0087	0.0675	0.1488
VOLUME	229.3966	649.6350	11.8434	45.0639	155.1448
RET	0.0766	0.7156	−0.2520	−0.0292	0.2253
absEARN	0.0758	0.1123	0.0141	0.0352	0.0868
ROA	0.0441	0.1334	0.0229	0.0626	0.1031
LOSS	0.2696	0.4437	0.0000	0.0000	1.0000

Notes: This table presents the mean, standard deviation, Q1 median and Q3 for firm characteristics. All the continuous variables (except RET) are winsorized at top and bottom 1% of respective annual distributions. The definitions of variables are presented in Table 1.

Table 3 presents the Pearson correlations. COVRGE is significantly correlated with all variables (the largest correlations of COVERGE are with LMV and VOLUME) in Equation (1), indicating the need to control for these firm characteristics in our analysis. There is a 0.35 correlation between RDG_ROE and DIFROA, suggesting that our measures of reporting bias resulting from expensing of R&D capture the same phenomena, to a large extent. RND has high positive correlations with RDG_ROE and DIFROA, suggesting that high-R&D firms have a high reporting bias arising from expensing of R&D (i.e., correlations between RND and RDG_ROE and DIFROA are both 0.39). There is a 0.40 correlation between STDROA and STDRET, indicating that our measures of uncertainty are highly correlated. There are also high correlations between RND and our measures of uncertainty, STDROA and STDRET, suggesting that uncertainty increases with R&D intensity (Lev 2001; Kothari et al. 2002). Moreover, there is high correlations between some of the cross-sectional determinants. For example, the correlation between LMV and VOLUME is 0.46. This finding raises the possibility that some of the cross-sectional determinants may not be independent. Hence, we need to perform a combined analysis of cross-sectional determinants to test whether one cross-sectional determinant subsumes the other.

Table 3. Pearson Correlations.

		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**
1	COVRGE	1.00																
2	RDG_ROE	−0.09	1.00															
3	DIFROA	0.10	0.35	1.00														
4	RND	0.05	0.39	0.39	1.00													
5	STDROA	−0.13	0.36	−0.03	0.36	1.00												
6	STDRET	−0.20	0.37	0.08	0.27	0.40	1.00											
7	ADV	0.14	−0.03	**0.01**	−0.05	**−0.01**	−0.06	1.00										
8	DEPR	0.17	0.10	0.02	0.11	0.04	0.06	−0.03	1.00									
9	INTANA	0.12	−0.04	−0.05	−0.06	−0.07	−0.16	0.07	0.17	1.00								
10	GDWLA	0.12	−0.07	−0.05	−0.08	−0.10	−0.17	0.02	0.10	0.88	1.00							
11	LMV	0.65	−0.27	**0.00**	−0.06	−0.26	−0.37	0.10	0.21	0.25	0.24	1.00						
12	DISSUE	0.02	**−0.01**	0.02	0.02	**0.00**	0.02	**0.01**	**0.00**	−0.05	−0.04	**0.00**	1.00					
13	GROWTH	0.07	0.28	0.29	0.12	0.13	0.16	0.03	0.05	**0.01**	**−0.01**	−0.02	0.04	1.00				
14	VOLUME	0.50	−0.05	**0.00**	0.07	−0.02	−0.05	0.08	0.18	0.12	0.12	0.46	**0.01**	**0.00**	1.00			
15	RET	−0.02	−0.09	−0.03	0.02	0.04	0.22	**−0.01**	−0.02	−0.02	−0.03	0.11	0.03	−0.04	**0.00**	1.00		
16	absEARN	−0.11	0.32	0.04	0.28	0.60	0.40	**−0.01**	0.04	−0.10	−0.13	−0.22	**0.01**	0.09	**−0.01**	0.12	1.00	
17	ROA	0.17	−0.56	**0.00**	−0.37	−0.39	−0.30	0.07	−0.07	**0.01**	0.03	0.26	0.04	0.08	0.07	0.05	−0.21	1.00
18	LOSS	−0.15	0.53	0.09	0.37	0.38	0.37	−0.05	0.10	−0.04	−0.06	−0.32	−0.03	0.03	−0.05	−0.11	0.35	−0.57

Notes: This table represents Pearson correlations. Bold correlations are NOT significant at 5%. The definitions of variables are presented in Table 1.

5. Empirical Results

5.1. The Relationship between R&D and Analyst Coverage

In this section, we present the results of investigating the relationship between R&D and analyst coverage, following Barth et al. (2001). Table 4 presents the pooled cross-sectional OLS regression results of Equation (1). We cluster firm-year observations by firm to eliminate autocorrelation (Petersen 2009). In all estimations we include year and industry indicator variables to eliminate year and industry fixed effects. We include industry dummies based on Fama and French (1997) for 48 industry classification in all estimations. The coefficient estimate of RND is 6.3625 (p-value < 0.01) when we use STDROA as the measure of uncertainty and this coefficient is 6.2832 (p-value < 0.01) when we use STDRET as the measure of uncertainty. Thus, we find that there is a positive association between R&D and analyst coverage consistent with Barth et al. (2001). The results in Table 4 show that one standard deviation increase in R&D leads to a roughly 0.92 increase in analyst coverage. Given that the mean and median analyst coverage are 10.37 and 7.00 in Table 2, this result suggests that R&D has an economically significant impact on analyst coverage.

Table 4. The Relationship between R&D and Analyst Coverage.

	UNCRTNY = STDROA		UNCRTNY = STDRET	
	Coefficient	**t-Stat**	**Coefficient**	**t-Stat**
RND	6.3625	7.70 ***	6.2832	7.63 ***
UNCRTNY	1.6336	2.97 ***	6.9186	7.84 ***
ADV	17.3490	3.98 ***	17.1847	3.94 ***
DEPR	−2.5786	−0.74	−3.1307	−0.91
INTANA	−0.5106	−0.52	−0.3805	−0.39
GDWLA	2.9755	2.38 **	3.0339	2.43 **
LMV	3.1076	25.91 ***	3.1700	26.14 ***
DISSUE	0.0898	0.50	0.0857	0.48
GROWTH	2.9111	8.09 ***	2.6444	7.54 ***
VOLUME	0.0032	10.18 ***	0.0032	10.05 ***
RET	−1.0749	−13.21 ***	−1.2294	−13.91 ***
absEARN	0.6936	1.93 *	0.7506	1.77 *
ROA	1.5209	2.33 **	1.6720	2.61 ***
LOSS	1.1663	7.94 ***	1.0474	7.27 ***
Clustering	Yes		Yes	
Year and industry fixed effects	Yes		Yes	
n	29,203		29,203	
R^2	0.5834		0.5846	

$$COVRGE_{it} = \beta_0 + \beta_1 RND_{it} + \beta_2 UNCRTNY_{it} + \beta_3 ADV_{it} + \beta_4 DEPR_{it} + \beta_5 INTANA_{it} + \beta_6 GDWLA_{it} + \beta_7 LMV_{it} + \beta_8 DISSUE_{it} + \beta_9 GROWTH_{it} + \beta_{10} VOLUME_{it} + \beta_{11} RET_{it} + \beta_{12} absEARN_{it} + \beta_{13} ROA_{it} + \beta_{14} LOSS_{it} + \varepsilon_{it} \quad (1)$$

Notes: *, **, *** statistically significant at the 10%, 5%, and 1% levels, respectively. This table presents pooled cross-sectional OLS regression results of Equation (1). UNCRTNY is measured with STDROA (STDRET) in the first (second) estimation. Firm-year observations are clustered by firm to eliminate autocorrelation, as per Petersen (2009). The definitions of the variables are presented in Table 1.

5.2. The Impact of Reporting Biases on the Relationship between R&D and Analyst Coverage

In this section we present the results of testing the impact of reporting biases under expensing of R&D compared to that under capitalization of R&D on the relationship between R&D and analyst coverage, to test H1. Table 5 presents the pooled cross-sectional OLS estimation results of Equation (2a). We perform two estimations. In the first estimation we use RDG_ROE as the measure of reporting bias. The coefficient estimate of RND in the first estimation is 10.1776 (p-value < 0.01), suggesting that there is a positive association between R&D and analyst coverage for neutral firms. The coefficient estimate of RND×AGRSV is −0.9917 and insignificant, suggesting that there is no significant difference in the association between R&D and analyst coverage across aggressive and neutral firms. However, the coefficient estimate of RNDS×CONSRV is −6.7095 (p-value < 0.01), suggesting that the association between R&D and analyst coverage is significantly lower for conservatively reporting firms compared to neutral firms. These results suggest that the association between R&D and analyst coverage is 66% smaller for conservative firms compared to that for neutral firms. Hence, the results in the first estimation suggest that H1 is rejected for conservatively reporting firms, while it is not rejected for aggressively reporting firms.

Table 5. The Impact of Reporting Biases on the Relationship between R&D and Analyst Coverage.

	RDG_ROE		DIFROA	
	Coefficient	**t-Stat**	**Coefficient**	**t-Stat**
AGRSV	−0.3475	−1.66 *	0.7380	3.87 ***
CONSRV	1.4969	7.22 ***	3.3702	10.66 ***
RND	10.1776	7.76 ***	12.9633	7.52 ***
STDROA	1.7083	3.12 ***	2.1477	3.52 ***
ADV	16.8436	3.87 ***	17.2231	3.77 ***
DEPR	−3.5622	−1.03	−2.3839	−0.66
INTANA	−0.7058	−0.72	−0.6399	−0.62
GDWLA	3.1307	2.51 **	4.0632	3.10 ***
LMV	3.1381	25.83 ***	3.1266	25.38 ***
DISSUE	0.0679	0.38	0.0969	0.52
GROWTH	2.3000	7.10 ***	2.1522	5.43 ***
VOLUME	0.0032	10.10 ***	0.0031	9.93 ***
RET	−1.0654	−13.30 ***	−1.0523	−12.18 ***
absEARN	0.6287	1.73 *	0.5030	1.31
ROA	1.2945	2.10 **	0.8083	1.12
LOSS	0.8369	5.28 ***	1.0648	6.97 ***
RND×AGRSV	−0.9917	−0.54	−7.3558	−4.97 ***
RND×CONSRV	−6.7095	−5.96 ***	−11.8126	−7.17 ***
Clustering	Yes		Yes	
Year and industry fixed effects	Yes		Yes	
n	29,203		27,242	
R^2	0.5860		0.5927	

$$COVRGE_{it} = \beta_0 + \beta_1 AGRSV_{it} + \beta_2 CONSRV_{it} + \beta_3 RND_{it} + \beta_4 UNCRTNY_{it} + \beta_5 ADV_{it} + \beta_6 DEPR_{it} + \beta_7 INTANA_{it} + \beta_8 GDWLA_{it} + \beta_9 LMV_{it} + \beta_{10} DISSUE_{it} + \beta_{11} GROWTH_{it} + \beta_{12} VOLUME_{it} + \beta_{13} RET_{it} + \beta_{14} absEARN_{it} + \beta_{15} ROA_{it} + \beta_{16} LOSS_{it} + \beta_{17} RND_{it} \times AGRSV_{it} + \beta_{18} RND_{it} \times CONSRV_{it} + \varepsilon_{it} \quad (2a)$$

Notes: *, **, *** statistically significant at the 10%, 5%, and 1% levels, respectively. This table presents pooled cross-sectional OLS regression results of Equation (2a). Reporting bias from expensing of R&D is measured with RDG_ROE in the first estimation and DIFROA in the second estimation. In all estimations we include year and industry indicator variables. Firm-year observations are clustered by firm to eliminate autocorrelation, as per Petersen (2009). The definitions of the variables are presented in Table 1.

The second estimation presents the results when we use DIFROA as the measure of reporting bias from expensing of R&D compared to capitalization of R&D. The coefficient estimate of RND is 12.9633 (p-value < 0.01), suggesting that there is a positive association between R&D and analyst coverage for neutral firms. The coefficient estimate of RND×AGRSV is −7.3558 (p-value < 0.01), suggesting that the association between R&D and analyst coverage is significantly lower for aggressively reporting firms compared to that for neutral firms. That is, the association between R&D and analyst coverage is 57% lower for aggressively reporting firms compared to that for neutral firms. The coefficient estimate of RND×CONSRV is −11.8126 (p-value < 0.01), suggesting that the association between R&D and analyst coverage is significantly lower for conservatively reporting firms compared to that for aggressively reporting firms. That is, the association between R&D and analyst coverage is 91% lower for conservatively reporting firms compared to that for neutral firms. The results in the second estimation suggest that H1 is rejected for both aggressively reporting and conservatively reporting firms. However, the results are stronger for conservatively reporting firms compared to those for aggressively reporting firms. In Table 5, we find that aggressively reporting firms have a significantly lower association between R&D and analyst coverage than neutral firms when we use DIFROA as the measure of reporting bias, but there is no significant difference when we use RDG_ROE as the measure of reporting bias. The differences in results could be due to the fact that DIFROA is a better measure of reporting bias under expensing of R&D compared to that under capitalization of R&D than RDG_ROE because DIFROA directly captures bias in earnings under expensing of R&D compared to that under capitalization of R&D, while RDG_ROE only captures the difference between annualized R&D growth with ROE. In Table 5, we use STDROA as the measure of uncertainty. However, the results are similar when we use STDRET as the measure of uncertainty. For brevity, we only report the results with STDROA. Overall, the results in Table 5 suggest that reporting biases from expensing of R&D compared to capitalization of R&D lead to a lower association between R&D and analyst coverage, rejecting H1. However, the impact of reporting biases is stronger for conservatively reporting firms than for aggressively reporting firms.

It is worth noting that the coefficient estimates of RND (Table 5) are positive and highly significant in both estimations of reporting biases, suggesting that the positive association between R&D and analyst coverage documented by Barth et al. (2001) is not explained by reporting biases under expensing of R&D compared to those under capitalization of R&D.

5.3. The Impact of Uncertainty on the Relationship between R&D and Analyst Coverage

In this section, we investigate the impact of uncertainty on the association between R&D and analyst coverage, to test H2. Table 6 presents the coefficient estimates from the pooled cross-sectional OLS estimation of Equation (2b). The first estimation presents the results when we measure uncertainty using the standard deviation of earnings, STDROA. The coefficient estimate of RND×UNCRTNY is −24.9130 (p-value < 0.01), indicating that the association between R&D and analyst coverage decreases with the uncertainty. Therefore, these results suggest that the uncertainty has a statistically significant impact on analyst coverage for R&D firms. Accordingly, H2 is rejected. The next estimation in Table 6 presents the results when we measure the uncertainty with volatility of monthly stock returns, STDRET. The coefficient estimate of RND×UNCRTNY is −43.9869 (p-value < 0.01), suggesting that the association between R&D and analyst coverage decreases with uncertainty. Overall, the results in Table 6 suggest that the uncertainty reduces the association between R&D and analyst coverage. Accordingly, H2 is rejected in favor of alternative.

Table 6. The Impact of Uncertainty on the Relationship between R&D and Analyst Coverage.

	UNCRTNY = STDROA		**UNCRTNY = STDRET**	
	Coefficient	**t-Stat**	**Coefficient**	**t-Stat**
RND	9.9464	9.15 ***	13.5122	10.34 ***
UNCRTNY	7.1326	7.51 ***	14.1497	11.55 ***
ADV	16.4610	3.80 ***	16.6772	3.83 ***
DEPR	−3.4449	−1.00	−3.5956	−1.05
INTANA	−0.6148	−0.63	−0.4492	−0.46
GDWLA	3.3096	2.66 ***	3.2811	2.64 ***
LMV	3.1302	26.18 ***	3.2057	26.40 ***
DISSUE	0.0721	0.41	0.0697	0.40
GROWTH	2.8588	7.98 ***	2.5868	7.39 ***
VOLUME	0.0032	10.11 ***	0.0031	9.94 ***
RET	−1.1014	−13.46 ***	−1.2120	−13.80 ***
absEARN	0.4560	1.27	0.7418	1.79 *
ROA	0.9320	1.50	1.1538	1.87 *
LOSS	0.9891	6.69 ***	0.9514	6.59 ***
RND×UNCRTNY	−24.9130	−7.66 ***	−43.9869	−9.27 ***
Clustering	Yes		Yes	
Year and industry fixed effects	Yes		Yes	

Table 6. *Cont.*

	UNCRTNY = STDROA		UNCRTNY = STDRET	
	Coefficient	**t-Stat**	**Coefficient**	**t-Stat**
n	29,203		29,203	
R^2	0.5856		0.5874	

$$\text{COVRGE}_{it} = \beta_0 + \beta_1\text{RND}_{it} + \beta_2\text{UNCRTNY}_{it} + \beta_3\text{ADV}_{it} + \beta_4\text{DEPR}_{it} + \beta_5\text{INTANA}_{it} + \beta_6\text{GDWLA}_{it} + \beta_7\text{LMV}_{it} + \beta_8\text{DISSUE}_{it} + \beta_9\text{GROWTH}_{it} + \beta_{10}\text{VOLUME}_{it} + \beta_{11}\text{RET}_{it} + \beta_{12}\text{absEARN}_{it} + \beta_{13}\text{ROA}_{it} + \beta_{14}\text{LOSS}_{it} + \beta_{15}\text{RND}_{it} \times \text{UNCRTNY}_{it} + \varepsilon_{it} \quad (2b)$$

Notes: *, *** statistically significant at the 10%, and 1% levels, respectively. This table presents pooled cross-sectional OLS regression results of Equation (2b). UNCRTNY is measured with STDROA (STDRET) in the first (second) estimation. In all estimations we include year and industry indicator variables. Firm-year observations are clustered by firm to eliminate autocorrelation, as per Petersen (2009). The definitions of the variables are presented in Table 1.

Another important result in Table 6 is that the coefficient estimate of RND remains positive and highly significant in both estimations of uncertainty, suggesting that the positive association between R&D and analyst coverage documented by Barth et al. (2001) is not explained by the uncertainty associated with R&D.

5.4. The Impact of Investors' Attention on the Relationship between R&D and Analyst Coverage

In this section we investigate the impact of investors' attention on the association between R&D and analyst coverage, to test for H3. Table 7 presents the coefficient estimates from the pooled cross-sectional OLS estimation of Equation (2c). The first estimation presents the results when we measure the uncertainty by the standard deviation of earnings, STDROA. The coefficient estimate of RND×VOLUME is positive and significant (0.0077; p-value < 0.01), indicating that the association between R&D and analyst coverage increases with investors' attention. Therefore, the results suggest that investors' attention has a statistically significant impact on analyst coverage for R&D firms. Accordingly, H3 is supported. The second estimation presents the results when we use STDRET as the measure of uncertainty. The coefficient estimate of RND×VOLUME remains positive and significant (0.0078; p-value < 0.01), suggesting that the association between R&D and analyst coverage increases with investors' attention.

Table 7. The Impact of Investors' Attention on the Relationship between R&D and Analyst Coverage.

	UNCRTNY = STDROA		UNCRTNY = STDRET	
	Coefficient	**t-Stat**	**Coefficient**	**t-Stat**
RND	4.5795	5.53 ***	4.4773	5.43 ***
UNCRTNY	1.7312	3.16 ***	7.1822	8.15 ***
ADV	16.8637	3.91 ***	16.6910	3.86 ***
DEPR	−3.2862	−0.96	−3.8699	−1.13
INTANA	−0.6957	−0.71	−0.5623	−0.57
GDWLA	2.8662	2.30 **	2.9230	2.35 **
LMV	3.1185	25.80 ***	3.1832	26.02 ***
DISSUE	0.0721	0.41	0.0675	0.38
GROWTH	2.9694	8.26 ***	2.6953	7.69 ***
VOLUME	0.0021	4.95 ***	0.0020	4.81 ***
RET	−1.0756	−13.19 ***	−1.2360	−13.91 ***
absEARN	0.6333	1.75 *	0.7082	1.67 *
ROA	1.1713	1.80 *	1.3172	2.07 **
LOSS	1.1965	8.17 ***	1.0735	7.49 ***
RND×VOLUME	0.0077	4.05 ***	0.0078	4.14 ***
Clustering	Yes		Yes	
Year and industry fixed effects	Yes		Yes	
n	29,203		29,203	

Table 7. *Cont.*

	UNCRTNY = STDROA		UNCRTNY = STDRET	
	Coefficient	**t-Stat**	**Coefficient**	**t-Stat**
R^2	0.5867		0.5880	
$COVRGE_{it} = \beta_0 + \beta_1 RND_{it} + \beta_2 UNCRTNY_{it} + \beta_3 ADV_{it} + \beta_4 DEPR_{it} + \beta_5 INTANA_{it} + \beta_6 GDWLA_{it} + \beta_7 LMV_{it} + \beta_8 DISSUE_{it} + \beta_9 GROWTH_{it} + \beta_{10} VOLUME_{it} + \beta_{11} RET_{it} + \beta_{12}\, absEARN_{it} + \beta_{13} ROA_{it} + \beta_{14} LOSS_{it} + \beta_{15} RND_{it} \times VOLUME_{it} + \varepsilon_{it}$				(2c)

Notes: *, **, *** statistically significant at the 10%, 5%, and 1% levels, respectively. This table presents pooled cross-sectional OLS regression results of Equation (2c). UNCRTNY is measured with STDROA (STDRET) in the first (second) estimation. In all estimations we include year and industry indicator variables. Firm-year observations are clustered by firm to eliminate autocorrelation, as per Petersen (2009). The definitions of the variables are presented in Table 1.

In addition, the coefficient estimate of RND is 4.5795 (p-value < 0.01) in the first estimation and 4.4773 (p-value < 0.01) in the second estimation, both of which are smaller than the coefficient estimates in Table 4 (i.e., the coefficient estimates of RND are roughly one-third smaller in Table 7 compared to those in Table 4). These results suggest that investors' attention seems to partially explain the positive association between R&D and analyst coverage documented by Barth et al. (2001).

5.5. The Impact of the Scale Effect on the Relationship between R&D and Analyst Coverage

In this section we investigate the impact of the scale effect of R&D on the association between R&D and analyst coverage, to test for H4. Table 8 presents the coefficient estimates from the pooled cross-sectional OLS estimation of Equation (2d). The first estimation presents the results when we measure the uncertainty using the standard deviation of earnings, STDROA. The coefficient estimate of RND×LMV is 3.3006 (p-value < 0.01), indicating that the association between R&D and analyst coverage increases with firm size. Therefore, the results suggest that the scale effect of R&D has a statistically significant impact on analyst coverage for R&D firms. Accordingly, H4 is supported. The second estimation presents the results when we utilize STDRET as the measure of uncertainty. The coefficient estimate of RND×LMV remains positive and highly significant (3.2974; p-value < 0.01), suggesting that the association between R&D and analyst coverage increases with the scale effect of R&D.

Table 8. The Impact of Scale Effects of R&D on the Relationship between R&D and Analyst Coverage.

	UNCRTNY = STDROA		UNCRTNY = STDRET	
	Coefficient	**t-Stat**	**Coefficient**	**t-Stat**
RND	−13.9495	−5.42 ***	−13.9814	−5.47 ***
UNCRTNY	2.2213	3.95 ***	7.3004	8.28 ***
ADV	17.4327	4.01 ***	17.3117	3.98 ***
DEPR	−3.2119	−0.94	−3.8179	−1.12
INTANA	−0.8668	−0.88	−0.7195	−0.73
GDWLA	3.1702	2.53 **	3.1987	2.56 ***
LMV	2.8138	22.01 ***	2.8768	22.29 ***
DISSUE	0.0567	0.32	0.0512	0.29
GROWTH	2.7268	7.47 ***	2.4740	6.98 ***
VOLUME	0.0030	9.62 ***	0.0029	9.49 ***
RET	−1.1594	−13.41 ***	−1.3223	−14.08 ***
absEARN	0.7711	2.11 **	1.0553	2.50 **
ROA	−0.0712	−0.12	0.0003	0.00
LOSS	1.0700	7.19 ***	0.9453	6.50 ***
RND×LMV	3.3006	7.36 ***	3.2974	7.39 ***
Clustering	Yes		Yes	

Table 8. *Cont.*

	UNCRTNY = STDROA		UNCRTNY = STDRET	
	Coefficient	**t-Stat**	**Coefficient**	**t-Stat**
Year and industry fixed effects	Yes		Yes	
n	29,203		29,203	
R^2	0.5892		0.5904	

$$COVRGE_{it} = \beta_0 + \beta_1 RND_{it} + \beta_2 UNCRTNY_{it} + \beta_3 ADV_{it} + \beta_4 DEPR_{it} + \beta_5 INTANA_{it} + \beta_6 GDWLA_{it} + \beta_7 LMV_{it} + \beta_8 DISSUE_{it} + \beta_9 GROWTH_{it} + \beta_{10} VOLUME_{it} + \beta_{11} RET_{it} + \beta_{12} absEARN_{it} + \beta_{13} ROA_{it} + \beta_{14} LOSS_{it} + \beta_{15} RND_{it} \times LMV_{it} + \varepsilon_{it} \quad (2d)$$

Notes: **, *** statistically significant at the 5%, and 1% levels, respectively. This table presents pooled cross-sectional OLS regression results of Equation (2d). UNCRTNY is measured with STDROA (STDRET) in the first (second) estimation. In all estimations we include year and industry indicator variables. Firm-year observations are clustered by firm to eliminate autocorrelation, as per Petersen (2009). The definitions of the variables are presented in Table 1.

In addition, the coefficient estimate of RND is −13.9495 (p-value < 0.01) in the first estimation and −13.9814 (p-value < 0.01) in the second estimation. These results suggest that after controlling for the impact of the scale effects of R&D on analyst coverage for R&D firms, the positive association between R&D and analyst coverage documented by Barth et al. (2001) disappears. In fact, the positive association between R&D and analyst coverage documented by Barth et al. (2001) turns into a negative association. These findings suggest that the scale effects of R&D seem to fully explain the positive association between R&D and analyst coverage documented by Barth et al. (2001).

5.6. The Combined Effects of All Cross-Sectional Determinants on the Relationship between R&D and Analyst Coverage

In previous tables we present the impact of cross-sectional determinants on the relationship between R&D and analyst coverage on a stand-alone basis (one determinant at a time). However, cross-sectional determinants may not be independent of each other. If this is the case, the presence of one cross-sectional determinant may subsume the impact of the other. To explore whether cross-sectional determinants have independent effects on the relationship between R&D and analyst coverage, we investigate the combined effects of all cross-sectional determinants. We estimate the following equation:

$$\begin{aligned} COVRGE_{it} = \beta_0 + \beta_1 AGRSV_{it} + \beta_2 CONSRV_{it} + \beta_3 RND_{it} + \beta_4 UNCRTNY_{it} + \beta_5 ADV_{it} + \beta_6 DEPR_{it} \\ + \beta_7 INTANA_{it} + \beta_8 GDWLA_{it} + \beta_9 LMV_{it} + \beta_{10} DISSUE_{it} + \beta_{11} GROWTH_{it} + \beta_{12} VOLUME_{it} + \beta_{13} RET_{it} \\ + \beta_{14} absEARN_{it} + \beta_{15} ROA_{it} + \beta_{16} LOSS_{it} + \beta_{17} RND_{it} \times AGRSV_{it} + \beta_{18} RND_{it} \times CONSRV_{it} \\ + \beta_{19} RND_{it} \times UNCRTNY_{it} + \beta_{20} RND_{it} \times VOLUME_{it} + \beta_{21} RND_{it} \times LMV_{it} + \varepsilon_{it} \end{aligned} \quad (3)$$

Tables 9 and 10 report the pooled cross-sectional OLS estimation results of Equation (3). In Table 9, we use RDG_ROE as our measure of reporting biases arising from expensing of R&D. The first (second) estimation in Table 9 presents the results when we measure uncertainty using STDROA (STDRET). Similar to the results in the Table 5 in the stand-alone analysis, the coefficient estimate of RDA×CONSRV remains negative and significant and the coefficient estimate of RDA×AGRSV remains insignificant in both estimations in Table 9, suggesting that conservative reporting has a negative effect on the relationship between R&D and analyst coverage but that aggressive reporting has no significant effect. Therefore, the effect of reporting biases on analyst coverage for conservatively reporting firms is not subsumed with the inclusion of the other cross-sectional determinants. Therefore, reporting biases seem to be an independent cross-sectional determinant of analyst coverage for R&D firms. In addition, similar to the results in Table 6 in the stand-alone analysis, the coefficient estimate of RDA×UNCRTNY remains negative and significant in both estimations, suggesting that uncertainty decreases the association between R&D and analyst coverage even when we include the other cross-sectional determinants in the estimation. Taken together, the inclusion of the other cross-sectional determinants does not subsume the impact of uncertainty on the relationship between R&D and analyst coverage. Thus, the uncertainty associated with R&D seem to be an independent cross-sectional determinant of analyst coverage for R&D firms.

Table 9. The Cross-sectional Determinants of Analyst Coverage for R&D Firms—RDG_ROE.

	UNCRTNY = STDROA		UNCRTNY = STDRET	
	Coefficient	**t-Stat**	**Coefficient**	**t-Stat**
AGRSV	−0.2490	−1.21	−0.1362	−0.66
CONSRV	1.2234	6.19 ***	1.1556	5.98 ***
RND	−3.6306	−1.22	−0.2036	−0.07
UNCRTNY	5.5276	6.45 ***	11.6291	10.61 ***
ADV	16.1680	3.74 ***	16.2661	3.75 ***
DEPR	−4.6332	−1.37	−4.9438	−1.46
INTANA	−1.0899	−1.11	−0.9066	−0.92
GDWLA	3.3878	2.71 ***	3.3578	2.70 ***
LMV	2.9494	21.82 ***	3.0237	22.08 ***
DISSUE	0.0293	0.17	0.0253	0.15
GROWTH	2.1905	6.72 ***	2.0514	6.36 ***
VOLUME	0.0024	5.36 ***	0.0024	5.23 ***
RET	−1.1408	−13.47 ***	−1.2642	−14.02 ***
absEARN	0.5299	1.44	1.0084	2.37 **
ROA	−0.0699	−0.12	−0.0569	−0.10
LOSS	0.7097	4.47 ***	0.6749	4.29 ***
RND×AGRSV	−1.8847	−1.10	−2.3319	−1.38
RND×CONSRV	−4.8911	−4.91 ***	−4.9853	−5.08 ***
RND×UNCRTNY	−14.8881	−5.43 ***	−29.5679	−8.34 ***
RND×VOLUME	0.0039	1.74 *	0.0040	1.81 *
RND×LMV	2.2782	4.18 ***	2.1759	4.03 ***
Clustering	Yes		Yes	
Year and industry fixed effects	Yes		Yes	
n	29,203		29,203	
R^2	0.5925		0.5940	

$$COVRGE_{it} = \beta_0 + \beta_1 AGRSV_{it} + \beta_2 CONSRV_{it} + \beta_3 RND_{it} + \beta_4 UNCRTNY_{it} + \beta_5 ADV_{it} + \beta_6 DEPR_{it} + \beta_7 INTANA_{it} + \beta_8 GDWLA_{it} + \beta_9 LMV_{it} + \beta_{10} DISSUE_{it} + \beta_{11} GROWTH_{it} + \beta_{12} VOLUME_{it} + \beta_{13} RET_{it} + \beta_{14}\, absEARN_{it} + \beta_{15} ROA_{it} + \beta_{16} LOSS_{it} + \beta_{17} RND_{it} \times AGRSV_{it} + \beta_{18} RND_{it} \times CONSRV_{it} + \beta_{19} RND_{it} \times UNCRTNY_{it} + \beta_{20} RND_{it} \times VOLUME_{it} + \beta_{21} RND_{it} \times LMV_{it} + \varepsilon_{it} \quad (3)$$

Notes: *, **, *** statistically significant at the 10%, 5%, and 1% levels, respectively. This table presents pooled cross-sectional OLS regression results of Equation (3). Reporting bias is measured with RDG_ROE. UNCRTNY is measured with STDROA (STDRET) in the first (second) estimation. In all estimations we include year and industry indicator variables. Firm-year observations are clustered by firm to eliminate autocorrelation, as per Petersen (2009). The definitions of the variables are presented in Table 1.

It is noted that the coefficient estimate of RND×VOLUME is only marginally significant in both estimations in Table 9 but that the coefficient estimate of RND×VOLUME is highly significant and positive in Table 7, in the stand-alone analysis. Therefore, the results in Table 9 suggest that inclusion of other cross-sectional determinants significantly subsumes the impact of investor attention on the relationship between R&D and analyst coverage. Finally, the coefficient estimate of RND×LMV is positive and highly significant in both estimations, consistent with the results in the stand-alone analysis in Table 8. These results suggest that inclusion of other cross-sectional determinants does not subsume the impact of scale effects of R&D on the relationship between R&D and analyst coverage. Therefore, scale effects of R&D seem to be an independent cross-sectional determinant of analyst coverage for R&D firms. Another interesting result in Table 9 is that the coefficient estimate of RND is insignificant in both estimations, suggesting that the positive association between R&D and analyst coverage documented by Barth et al. (2001) is fully explained by the cross-sectional determinants investigated in this study. To explore which particular cross-sectional determinant explains the positive association between R&D and analyst forecast, we drop the interaction of firm size with R&D and RND×LMV from Equation (3). We find that the coefficient estimate of RND is positive and highly significant. This result suggests that it is the scale effects of R&D that explain the positive relationship between R&D and analyst forecast documented by Barth et al. (2001).

Table 10 presents the pooled cross-sectional OLS estimation results of Equation (3) when we use DIFROA as our measure of reporting biases arising from expensing of R&D. The first (second) estimation presents the results when we measure uncertainty using STDROA (STDRET). Similar to the results in the stand-alone analysis in Table 5, the coefficient estimates of RDA×CONSRV and RND×AGRSV are both negative in both estimations in Table 10, suggesting that both conservative and aggressive reporting have a negative effect on the relationship between R&D and analyst coverage when we use DIFROA as our measure of reporting bias. The interactions of other cross-sectional determinants are similar to those in Table 9, except for the coefficient estimates of RND×VOLUME, which are insignificant in Table 10 even though they are marginally significant in Table 9. Overall, the results in Tables 9 and 10 suggest that cross-sectional determinants of analyst coverage do not subsume each other, except for investor attention, suggesting that the cross-sectional determinants considered in our paper have an independent effect on the relationship between R&D and analyst coverage. In addition, the coefficient estimate of RND is insignificant, consistent with that in Table 9, suggesting that scale effects of R&D explain the positive association between R&D and analyst coverage documented by Barth et al. (2001).

Table 10. The Cross-sectional Determinants of Analyst Coverage for R&D Firms—DIFROA.

	UNCRTNY = STDROA		**UNCRTNY = STDRET**	
	Coefficient	**t-Stat**	**Coefficient**	**t-Stat**
AGRSV	0.4072	2.18 ***	0.4490	2.40 ***
CONSRV	3.1355	10.13 ***	3.0487	9.88 ***
RND	−3.9618	−1.21	−1.0967	−0.33
UNCRTNY	5.2521	5.55 ***	10.7449	9.11 ***
ADV	16.7825	3.69 ***	16.8130	3.68 ***
DEPR	−3.6508	−1.03	−4.1087	−1.16
INTANA	−1.0653	−1.02	−0.8759	−0.84
GDWLA	4.2488	3.23 ***	4.1879	3.19 ***
LMV	2.9168	21.36 ***	2.9912	21.48 ***
DISSUE	0.0538	0.29	0.0529	0.29
GROWTH	2.0926	5.23 ***	1.8761	4.80 ***
VOLUME	0.0024	5.33 ***	0.0024	5.20 ***
RET	−1.1285	−12.34 ***	−1.2556	−12.94 ***
absEARN	0.5794	1.52	1.0656	2.39 **
ROA	−0.9209	−1.41	−0.7730	−1.20
LOSS	0.9304	6.06 ***	0.8657	5.74 ***
RND×AGRSV	−4.0245	−3.01 ***	−4.1019	−3.09 ***
RND×CONSRV	−10.2512	−6.64 ***	−10.0810	−6.56 ***
RND×UNCRTNY	−12.9627	−4.26 ***	−24.7823	−6.29 ***
RND×VOLUME	0.0035	1.50	0.0036	1.57
RND×LMV	2.6237	4.45 ***	2.5079	4.26 ***
Clustering	Yes		Yes	
Year and industry fixed effects	Yes		Yes	
n	27,242		27,242	
R^2	0.5992		0.6003	

Notes: **, *** statistically significant at the 5%, and 1% levels, respectively. This table presents pooled cross-sectional OLS regression results of Equation (3) (presented in Table 9). Reporting bias is measured with DIFROA. UNCRTNY is measured with STDROA (STDRET) in the first (second) estimation. In all estimations we include year and industry indicator variables. Firm-year observations are clustered by firm to eliminate autocorrelation, as per Petersen (2009). The definitions of the variables are presented in Table 1.

5.7. Endogeneity Analysis

For robustness, we re-estimate our main models while treating for possible endogeneity. In particular, to address potential reverse causality issues, we make use of the two-stage least squares (2SLS) regression analysis with an instrumental variable to correct for endogeneity. Since we use the R&D variable in our models both directly and as part of interactions, we follow Gupta et al. (2017) and use two instrumental variables. Specifically, we use our instrumental variable of choice as well as its interaction with the cross-sectional determinants of R&D. We follow Gupta et al. (2017) and use an instrumental variable which is the "mean R&D intensity using all the other firms in the same industry, country and year, however, without that firm into consideration" (p. 401). Gupta et al. (2017) argue that "the industry mean R&D intensity (without the particular firm in consideration) influences the firm's R&D intensity due to inter-industry spill-overs but it is unlikely to be correlated with the firm's Tobin's Q". (p. 401). Our results (untabulated) remain robust and consistent with the main analyses in our study.

We repeat the same 2SLS analysis using a different instrumental variable suggested by Rong and Xiao (2017), which is the effective state-level R&D tax credits in Table 1. Rong and Xiao (2017) define the instrument as "the effective R&D tax credit rate in state c in year $t-1$ where firm i is located" (p. 13). Rong and Xiao (2017) argue that the R&D tax credit instrument is valid "because the implementation of R&D tax credits should affect firms' innovations, but it should not directly affect firms' diversification decisions" (p. 4). Following the same logic, R&D tax credit should affect firms' R&D levels but not the analyst coverage. Our results (untabulated) remain robust and consistent with the main analyses in our study.

6. Conclusions

Barth et al. (2001) document a positive association between R&D and analyst coverage. However, they do not explore what particular attribute of R&D explains this positive association. In this paper, we attempt to fill this gap by investigating the cross-sectional determinants of the relationship between R&D and analyst coverage. We consider four cross-sectional determinants: reporting biases under expensing of R&D compared to capitalization of R&D, uncertainty associated with R&D, investors' attention, and scale effects of R&D. We find that reporting biases resulting from expensing of R&D decrease the association between R&D and analyst coverage and that the effect is stronger when a firm reports conservatively than when it reports aggressively. In addition, we find that the uncertainty associated with R&D decreases the association between analyst coverage and R&D. We also find that investors' attention and the scale effects of R&D increase the relationship between R&D and analyst coverage. When we perform combined analysis, we find that the impact of investors' attention is largely mitigated, while the other cross-sectional determinants are not affected. Finally, we find that the scale effect of R&D seems to explain the positive association between R&D and analyst coverage documented by Barth et al. (2001).

Our findings have implications for both academicians and standard-setters. Our paper complements Barth et al. (2001) in two ways. First, we extend Barth et al. (2001) by investigating cross-sectional determinants of the relationship between R&D and analyst coverage and identify four cross-sectional determinants. Second, we are able to identify what particular attribute of R&D explains the positive relationship between R&D and analyst coverage documented by Barth et al. (2001). Furthermore, our findings add to the literature on the negative consequences of expensing of R&D. The prior research primarily focuses on the demand for accounting information (i.e., the informativeness or usefulness of accounting information for equity investors). We complement the prior research by documenting the negative consequences of expensing of R&D on the supply of information by financial analysts. While some researchers suggest that financial analysts might eliminate the information gap in the financial statements resulting from expensing of R&D (Kimbrough 2007), our evidence suggests that analysts themselves are negatively affected by reporting biases. Therefore, they are less likely to eliminate the information gap in financial statements due to reporting biases resulting from expensing of R&D. Therefore, our findings suggest that the negative consequences of reporting biases could be more severe than those suggested in the prior literature. The U.S. is in the process of converging with IFRS, which allows the capitalization of R&D. Thus, our findings could provide useful insights to standard setters about the impact of expensing as compared to capitalizing of R&D.

In addition, our paper enhances the prior literature that investigates the implications of the uncertainty associated with R&D. Prior research suggests that the uncertainty associated with R&D affects many aspects of R&D firms such as stock and bond market valuations, insider gains and information asymmetry, value of analyst stock recommendations, stock return volatility, etc. We add to this literature by documenting the fact that the uncertainty associated with R&D also affects analyst coverage for R&D firms. Moreover, our paper enhances the existing literature about the scale effects of R&D. Prior research documents the fact that the scale effects of R&D affect productivity and future earnings associated with R&D investments. We document the fact that the scale effects of R&D also affect analyst coverage for R&D firms. Finally, our paper contributes to the prior literature about the impact of investors' attention on high-technology R&D firms. While prior research focuses on the impact of investors' attention on stock market valuation, we document the fact that investors' attention also affects analyst coverage for R&D firms.

Based on our findings, we suggest the following practical recommendations for R&D-intensive firms. First, R&D-intensive firms should enhance the transparency of their R&D expenditures and projects, to mitigate the negative effects of reporting biases and uncertainty on analyst coverage and to reduce adverse impact of expensing R&D. Second, R&D-intensive firms should actively communicate the potential and progress of their R&D activities, to attract and retain investor attention and analyst coverage. Third, firms with significant R&D investments should highlight the scale effects and potential future earnings, to positively influence analyst coverage.

While our study sheds light on the cross-sectional determinants of the relationship between R&D and analyst coverage, several areas remain open for further exploration. Future research could build on our findings in the following ways. First, future studies could examine how the relationship between R&D and analyst coverage evolves over time, particularly in response to changes in accounting standards or economic conditions. This would provide insights into the dynamic nature of this relationship. Second, with the U.S. moving towards convergence with the IFRS, which allows the capitalization of R&D, it would be valuable to compare the impact of different accounting treatments on analyst coverage across different jurisdictions. Such comparative studies could inform policymakers and standard setters about the broader implications of accounting choices. Finally, future research could investigate whether the determinants we identified vary across different sectors, such as biotechnology, pharmaceuticals, and technology. Sector-specific analyses could reveal unique factors influencing analyst coverage in these industries.

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Notes

1 For example, Shi (2003) suggests that bond holders demand a premium from R&D firms for greater uncertainty associated with R&D. Aboody and Lev (2000) suggest that the uncertainty associated with R&D leads to greater insider gains and greater information asymmetry. Palmon and Yezegel (2012) argue that the uncertainty associated with R&D affects the value of analyst stock recommendations for R&D firms. Chan et al. (2001) suggest that the uncertainty associated with R&D leads to greater stock return volatility.

2 Consistent with these arguments, Chan et al. (2001) suggest that the practice of immediately expensing R&D can have a substantial distortionary effect on earnings and book values for highly R&D-intensive firms. They also suggest that, as a result of expensing of R&D, some yardsticks commonly used by investors, such as price-earnings ratios and market-to-book ratios, may be mis-stated. Similarly, Lev (2004) suggests that that share prices of intangible-intensive companies command a large premium over book value because of expensing of R&D. Merkley (2014) suggests that financial statements have limited ability to communicate the value of R&D investments. In the same vein, Amir and Lev (1996) document the fact that while the total market value of equity of publicly traded sample cellular phone companies in their study was USD 34 billion, the median earnings and free cash flows of these companies were consistently negative from their inception, and their book values were so depressed as to yield a median market-to-book ratio of 12, which is more than five times the corresponding ratio of industrial companies.

3 Amir and Lev (1996) suggest that "while significant market values are created in technology sector, key financial variables, such as earnings and book values, are often negative or excessively depressed and appear unrelated to market values". (p. 4) They also document the fact that on a stand-alone basis, financial information (earnings, book values, and cash flows) are largely irrelevant for security valuation; however, nonfinancial indicators, such as POPS (total population in the licensed service area) (a growth proxy) and Market Penetration (an operating performance measure), are highly value-relevant.

4 An alternative to the expensing of R&D is the capitalization of R&D. SFAS No. 86 allows for the capitalization of software development costs in the software industry in the US. Aboody and Lev (1998) find that annually capitalized software development costs, under SFAS No. 86, are positively associated with stock returns and that the cumulative software assets reported on the balance sheet are priced by equity investors, suggesting that capitalization of R&D provides useful information for investors in equity valuation. Using bid–ask spread and share turnover as proxies for information asymmetry, Mohd (2005) finds that, after the introduction of SFAS No. 86, information asymmetry decreases for software firms relative to other high-tech firms. He also finds that, within the software industry, information asymmetry is significantly lower for firms that capitalize (capitalizers) than for those that expense (expensers) software development costs. Oswald and Zarowin (2007) find that stock prices are more informative for future earnings for capitalizers than for expensers, suggesting that capitalization is more informative than expensing of R&D. However, Cazavan-Jeny and Jeanjean (2006) find that capitalized costs are not value-relevant in France. In addition, Dinh et al. (2016) document the fact that capitalization of R&D can be used for earnings management.

5 The Financial Accounting Standards Board (FASB) suggests that future benefits of R&D are highly uncertain and, therefore, capitalization of R&D might actually mislead investors and lenders. The FASB states that "... evidence of a direct causal relationship between current research and development expenditures and subsequent future benefits generally has not been found... there is often a high degree of uncertainty about whether research and development expenditures will provide any future benefits" (FASB 1974, Statement No. 2, para. 49).

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