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Quadrophobia: Strategic Rounding of EPS Data

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Abstract

Managers' incentives to round up reported earnings per share (EPS) cause an underrepresentation of the number 4 in the first post-decimal digit of EPS, or "quadrophobia." We develop a novel measure of aggressive financial reporting practices based on a firm's history of quadrophobia. Quadrophobia is pervasive, persistent, and successfully predicts future restatements, Securities and Exchange Commission enforcement actions, and class action litigation. It is more pronounced when executive compensation is more closely tied to the stock price and when the firm anticipates violating debt covenants. Quadrophobia is especially strong when rounding-up EPS allows firms to meet analyst expectations, and investors seem not to see through this behavior.

I. Introduction

The disclosure of accurate and reliable information about firms' financial performance is important for the efficient functioning of capital markets, as it enables investors to make informed portfolio decisions that shift capital toward the most profitable investment projects. However, the preparation of financial

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statements and related disclosures inevitably involves the exercise of managerial judgment. The subjective determinations inherent in this process are vulnerable to a range of distortions, some of which reflect management's self-interest in generating financial data. Regulators and investors expend substantial resources to audit and monitor corporate financial reports in order to detect and deter inappropriate exercises of discretion. For the Securities and Exchange Commission (SEC), identifying and remedying accounting fraud serves its core mission to protect investors and promote trust in U.S. financial markets.[1]

Our article develops a novel and simple measure of an aggressive approach to financial reporting, which is based on the distribution of the first post-decimal digit in a company's earnings per share (EPS) data. This measure is predictive of problematic accounting practices that lead to restatements, enforcement actions, and class action securities fraud litigation, and has been successfully implemented by the SEC to initiate at least four enforcement proceedings alleging the exercise of managerial discretion in a manner that violates federal securities law (see Section IV.D for details on the SEC's investigations motivated by our measure).[2]

Our measure relies on the rounding convention used in reporting EPS data, which rounds EPS to the nearest cent. Earnings of 13.4 cents are rounded down to 13 cents, whereas earnings of 13.5 cents are rounded up to 14 cents. The amount of accounting discretion required to increase rounded EPS by 1 cent, all other factors equal, is minimized when the first digit to the right of the decimal in the EPS calculation is a 4. In this case, increasing unrounded EPS by a mere 10th of a cent by upwardly manipulating total earnings increases reported EPS by a full cent. We thus analyze the distribution of the first post-decimal digit in a company's EPS data and focus on the extent to which the number "4" is underrepresented in that position for evidence that management has consistently "rounded up" its reported EPS results. Consistent underrepresentation of the number 4 in a company's EPS (a pattern we call "quadrophobia") can signal an overall aggressive approach to financial reporting that could manifest itself in more serious violations, the hypothesis we examine and confirm in the data.

More precisely, we study the incidence of quadrophobia in quarterly earnings reports across all publicly traded firms over the period spanning from 1980 to 2021. We document that quadrophobia is pervasive: The number 4 is significantly underrepresented in the first post-decimal digit of EPS, particularly among firms that are covered by analysts. For example, although the frequency of the number 4 under the null hypothesis of no earnings management is 10%,[3] its frequency in reported EPS data of firms with analyst coverage is only 8.2%. We also show that firms engaging in quadrophobia adjust the measures of EPS that they target in response to both

[1]For example, "Insights into the SEC's Risk Assessment Programs" by Mark J. Flannery, Feb. 25, 2015.

[2]See "SEC Probes Whether Companies Rounded Up Earnings Per Share," *Wall Street Journal*, June 22, 2018; and "SEC Digs Deeper into Companies' EPS Manipulation," *Wall Street Journal*, Oct. 10, 2021. See also "Better to Round Up Than Down," by Matt Levine, *Bloomberg*, June 25, 2018; and the SEC press release 2020-226 "SEC Charges Companies, Former Executives as Part of Risk-Based Initiative" (Sept. 28, 2020).

[3]Section II explains in detail why the distribution of the first post-decimal digit of EPS in the absence of earnings management is uniform.

regulatory changes (in particular, the adoption of FAS 128, which acts as a shock that allows us to confirm our hypothesis; see Section II.C) and market participants' and analysts' shifting focus toward pro forma EPS (Section V.C).

We next document that quadrophobia is persistent: Companies with a history of rounding behavior are significantly more likely to continue the practice. In other words, certain managements are particularly likely to engage in strategic rounding and the phenomenon is not randomly distributed across all reporting companies.

Motivated by this finding, we construct a firm-level measure of aggressive financial reporting practices, the quadrophobia score (Q-score). For every firm-quarter observation, the Q-score measures the incidence of the number 4 in the first post-decimal digit of the firm's EPS over several preceding quarters (we generalize our results to other numbers in Section VII). Companies with high Q-scores have not reported a 4 over several prior quarters and hence are more likely to have engaged in strategic rounding. Compared with other commonly used earnings management proxies, this measure is extremely simple to construct and is highly transparent. Moreover, because our measure is based only on the statistical distribution of digits in EPS, it has the advantage of being a direct measure of aggressive accounting practices. This is important given the concern in the literature that accrual-based measures are systematically correlated with firm characteristics related to fundamental firm performance,[4] which may bias the inferences and leads McNichols (2000) to conclude that "future contributions to the earnings management literature will … exploit the distributional properties of earnings."

Importantly, we show that our quadrophobia measure strongly predicts future misconduct, as companies with high Q-scores are significantly more likely to restate their financial statements, be named as defendants in SEC Accounting and Auditing Enforcement Releases (AAERs), and be sued in class action securities fraud litigation. This result holds after controlling for measures of discretionary accruals and firm characteristics from several prominent predictive models developed in the literature (Dechow, Sloan, and Sweeney (1995), Beneish (1999), Kothari et al. (2005), Dechow, Ge, Larson, and Sloan (2011)). Using the receiver operating characteristics (ROC) methodology, we also show that the inclusion of the Q-score improves the ability of existing models to predict accounting misconduct. Thus, even if quadrophobia, on its own, represents the exercise of legitimate accounting discretion, it appears to signal an overall aggressive financial reporting culture that is practiced by managements that are more likely to engage in other problematic practices.

We also examine the economic incentives to engage in quadrophobia by identifying factors that motivate managements to round up their EPS data. We show that quadrophobia is stronger when executive compensation is more closely tied to the stock price, consistent with managers' incentives to increase the value of their stock and option portfolio by inflating earnings. Quadrophobia is also more pronounced among firms violating debt covenants in the quarters preceding the violation. Although we do not find that firms use quadrophobia to avoid covenant

[4]For the discussion of such concerns, see, e.g., McNichols (2000), Kothari, Leone, and Wasley (2005), Dechow, Ge, and Schrand (2010), and Owens, Wu, and Zimmerman (2017). See also Section VI for more details.

violations per se, we find suggestive evidence that firms round up EPS to project financial strength and thereby improve their bargaining position with creditors upon technical default (DeFond and Jiambalvo (1993), (1994)). Our analysis also highlights the role of capital market pressure and incentives to meet analyst expectations. In particular, strategic rounding is more likely to be practiced by firms that have analyst coverage, and the probability of quadrophobia at a given firm increases (decreases) when analyst coverage is initiated (dropped). We also show that firms engaging in quadrophobia focus on pro forma EPS, which is calculated by analysts to adjust earnings for nonrecurring items, rather than on GAAP EPS. Finally, quadrophobia is especially pronounced when the result of rounding allows firms to meet or narrowly beat analyst expectations. Moreover, we examine price reactions to earnings announcements and do not find evidence that investors "see through" this behavior: The price reaction to meeting or narrowly beating analyst forecasts is similar regardless of whether this target is achieved by rounding up or rounding down EPS, even among persistent quadrophobes. Over longer horizons, however, investors are not misled: Firms that meet or beat expectations by rounding up underperform those whose EPS is rounded down. Combined, our results are consistent with the opportunistic use of strategic rounding by publicly reporting companies.

Overall, quadrophobia appears to signal an aggressive financial reporting culture. Although strategic rounding may not involve inappropriate conduct on its own, it seems to be practiced by managements striving to meet analyst expectations, looking to increase their compensation by inflating earnings, and being more likely to engage in serious misconduct leading to SEC and private litigation activity. In this sense, our article is related to a broader finance literature that studies the link between financial fraud and overall firm culture, showing that culture manifests itself in different dimensions. According to a survey of CEOs and CFOs conducted by Graham, Grennan, Harvey, and Rajgopal (2022), 70% of executives indicate that culture plays a moderate or important role for the quality of their firm's financial reporting. Biggerstaff, Cicero, and Puckett (2015) document a link between option backdating and other questionable corporate activities, including financial fraud and narrowly beating analyst forecasts. Liu (2016) finds that firms with corruption culture, as measured by the cultural background of their insiders, are more likely to conduct accounting fraud and have abnormal accruals. Davidson, Dey, and Smith (2015) and Griffin, Kruger, and Maturana (2019) find a relationship between executives' personal behavior outside the workplace and their firms' propensity to restate earnings and commit fraud. Our article contributes to this literature by proposing a simple measure to identify firms with aggressive accounting cultures, which can be easily constructed for all publicly traded firms.

By introducing this measure, our research also contributes to an extensive literature that develops measures of earnings management and builds models to predict restatements, AAERs, and class action lawsuits. Researchers have used accrual quality, financial performance, capital market incentives, off-balance-sheet information, and corporate governance characteristics to predict accounting manipulation.[5] Differently from this literature, our article relies exclusively on the

[5]See Dechow, Sloan, and Sweeney (1995), (1996), Beneish (1999), Burns and Kedia (2006), Dechow et al. (2011), and Alawadhi, Karpoff, Koski, and Martin (2020), among others. Larcker and

distributional properties of EPS, a characteristic that has several advantages that we discuss in Section VI. Our measure helps predict accounting violations even after controlling for several prominent predictive models, and its inclusion increases these models' predictive accuracy. In a study subsequent to the earlier draft of our article, Amiram, Bozanic, and Rouen (2015) rely on Benford's law to construct the mean absolute deviation statistic based on the distribution of digits of all variables in the balance sheet, income statement, and cash flow statement. Unlike their measure, the quadrophobia score is very simple to construct and only requires data on firms' net income and number of shares. In addition, our measure is based on EPS, which is arguably one of the most relevant and susceptible to manipulation variables, whereas Amiram et al. (2015) do not analyze this variable.

Our focus on the distributional properties of EPS also relates our article to earlier studies identifying abnormal patterns in the distribution of earnings (Carslaw (1988), Thomas (1989), Burgstahler and Dichev (1997), Degeorge, Patel, and Zeckhauser (1999), and Burgstahler and Eames (2006)). We build on Craig (1992) and Das and Zhang (2003), who show that numbers below (above) 5 are underrepresented (overrepresented) in the first post-decimal digit of EPS, by developing a firm-level measure of earnings management that predicts serious accounting violations, thus allowing a simple tool to detect firms with aggressive accounting practices. We also highlight the economic importance of strategic rounding by documenting that it is sensitive to the benefits of inflating EPS related to managerial compensation, debt covenants, and analyst coverage.

Thus, more broadly, our article contributes to the literature analyzing managerial motives for earnings management.[6] We compare our results to those in this literature in Section V and highlight that the results for quadrophobia often differ from those in papers using other measures of earnings management. In particular, the incidence of quadrophobia appears to be relatively more sensitive to the benefits of inflating earnings (e.g., those related to executive compensation or to meeting analyst forecasts), which we explain by the relatively low costs of this form of earnings management. Moreover, our measure is well suited to study the motives for earnings management because it captures aggressive accounting practices directly, whereas tests based on abnormal accruals are joint tests of both the underlying theory tested and the model used to estimate abnormal accruals (see also the discussion in Section VI).

The article proceeds as follows: Section II introduces our methodology and presents evidence of strategic rounding. Section III develops the Q-score and shows that quadrophobia is persistent. Section IV documents the ability of the Q-score to

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Zakolyukina (2012) focus on linguistic features of management conference calls. Price, Sharp, and Wood (2011) compare commercially developed and academic risk measures. Bertomeu, Cheynel, Floyd, and Pan (2021) develop a machine learning approach. See Dechow et al. (2010) for a comprehensive discussion of this literature.

[6]This literature includes Bergstresser and Philippon (2006), Burns and Kedia (2006), Erickson, Hanlon, and Maydew (2006), and Armstrong, Jagolinzer, and Larcker (2010) on executive compensation; Yu (2008), Irani and Oesch (2013), (2016), and Chen, Harford, and Lin (2015) on analyst coverage; and DeAngelo, DeAngelo, and Skinner (1994), DeFond and Jiambalvo (1994), Dichev and Skinner (2002), and Sweeney (1994) on debt covenants. We provide a more comprehensive review of the literature in Section V.

predict serious financial misconduct. Section V studies the role of executive compensation, analyst coverage, and covenants. Section VI discusses the advantages and disadvantages of our measure relative to other measures in the literature, and Section VII provides robustness tests. Section VIII presents policy implications and concludes.

II. Evidence of Strategic Rounding Behavior

A. Data

We obtain our main sample from Compustat fundamental quarterly files for the period spanning from 1980 to 2021. We eliminate all observations with missing net income and number of shares used to calculate EPS, as well as observations with negative total assets and currency code not U.S. dollars. The resulting sample of 1,113,460 firm-quarter observations covers 28,459 firms. The sample size in the analysis that follows varies across tests and is generally smaller than this overall sample because of limited data on the variables used in those tests.

Analyst data are obtained from the IBES Summary database. For each firm-quarter observation, we capture the most recent consensus forecast prior to the earnings announcement date. Consensus analyst forecasts are available for approximately 45% of firm-quarter observations.

B. Identifying Strategic Rounding

Our earnings management measure is based on the observation that managers have an incentive to round up reported earnings, and this incentive manifests as an abnormal distribution of the first post-decimal digit of EPS expressed in cents. Specifically, EPS data are rounded up to the next highest cent if the first post-decimal digit is 5–9, but rounded down to the next lowest cent if that digit is 1–4. Because the amount of earnings management required to obtain an extra rounded cent of reported EPS is minimized when the first post-decimal digit is a 4, we hypothesize that earnings management through rounding causes an underrepresentation of the number 4 in the first post-decimal digit of EPS.

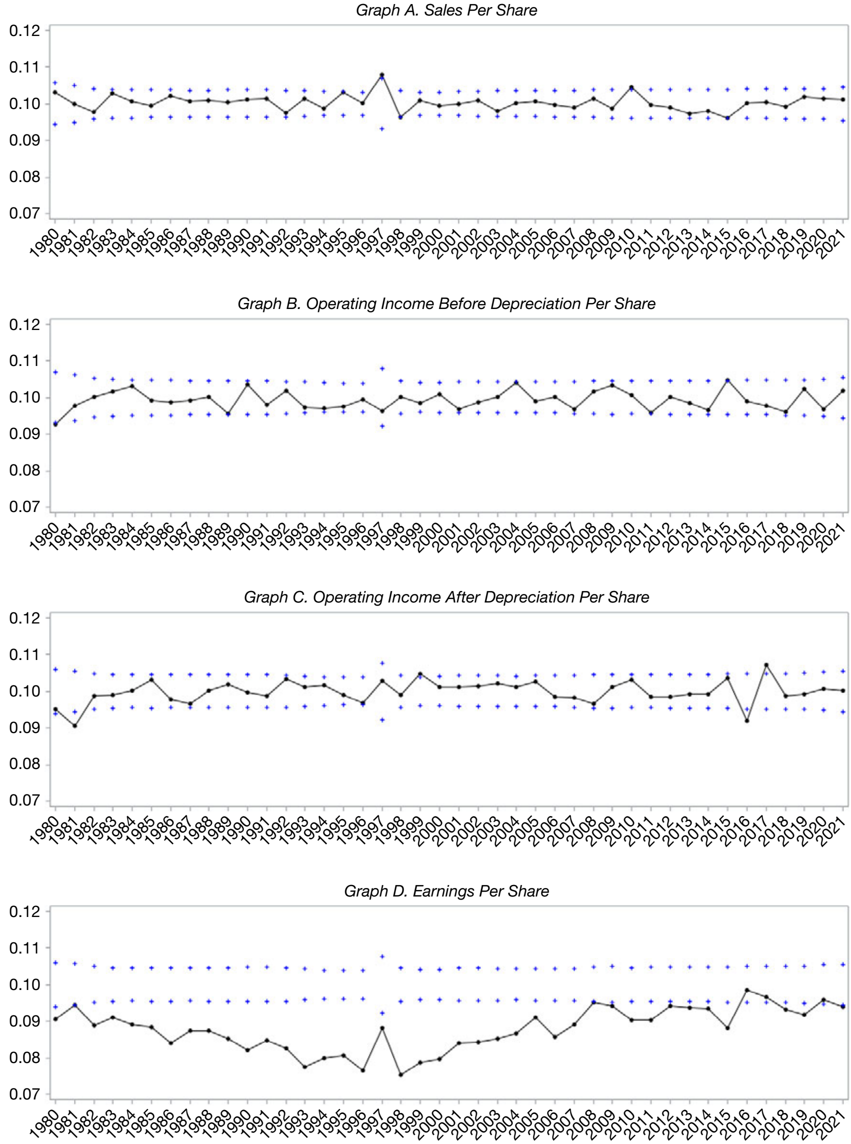
Our null hypothesis is that the distribution of numbers in the first post-decimal digit that prevails in the absence of earnings management is uniform and that numbers 0–9 should therefore each appear with frequency 0.1. We confirm that the uniform distribution is an appropriate null hypothesis by studying the distribution of the first post-decimal digit for per-share accounting data that do not regularly attract market attention and for which there is no incentive to manage through rounding: sales per share and operating income per share calculated both before and after depreciation (see Graphs A–C of Figure 1). The uniform distribution is also consistent with Benford's law.[7] To test the null hypothesis that the frequency of a given number in the first post-decimal digit is $p_0 = 0.1$, we apply the statistic

[7]Benford's law (Benford (1938)) suggests that in a random sample, the *first* digit of financial and other data series is distributed according to Benford's distribution, but that the distribution of the *n*th digit approaches the uniform distribution exponentially fast as *n* approaches infinity (Hill (1995)). Because the median quarterly EPS for observations with positive earnings is \$0.27 in our sample, the

FIGURE 1

Frequency of the Number 4 in the First Post-Decimal Digit

Figure 1 tests the hypothesis that the frequency of the number 4 in the first post-decimal digit of quarterly sales per share, operating income before and after depreciation per share, and earnings per share, all expressed in cents, is 0.1. The solid lines present the frequency of the number 4, and the blue "plus" marks present 95% confidence intervals around 0.1. Each per-share figure is calculated as the corresponding aggregate number, expressed in cents, divided by the number of common shares used to calculate EPS, where EPS is defined as primary EPS before 1997 and as diluted EPS starting in 1997. For each figure, the sample includes all firm-quarter observations for which the corresponding per-share number is greater than 0.1 cents.



first post-decimal digit of EPS expressed in cents is typically the third digit of EPS data in dollars, so its distribution should be close to uniform according to Benford's law.

$z = \frac{p - p_0}{\sqrt{\frac{p_0(1-p_0)}{n}}}$, where n is the sample size and p is the frequency of the number in the sample. Under the null hypothesis, z has a standard Normal distribution.[8]

We cannot use EPS data provided by Compustat to identify strategic rounding, as those data are already rounded to the nearest cent. To obtain the unrounded EPS expressed in cents, we multiply income after extraordinary items by 100 and divide by the number of common shares used to calculate EPS.[9] In our baseline analysis, we only consider observations with positive EPS values because we expect the pattern to reverse for negative values (see footnote 10 and Table A4 in the Supplementary Material). We also eliminate observations with EPS below 0.1 cents because the first post-decimal digit is always 0 in this case, which may bias upward the frequency of zeros and bias downward the frequency of other digits. This constraint eliminates fewer than 1% of observations, and the results are not sensitive to their inclusion.

Figure 1 illustrates the time-series frequency of the number 4 in the first post-decimal digit of several per-share data series, each expressed in cents. In all data series, except EPS, this frequency is statistically indistinguishable from 0.1 for the vast majority of years, consistent with the null hypothesis. In EPS data, however, the number 4 is substantially and consistently underrepresented. The lowest observed frequency is 0.075 in 1998, indicating that a quarter of the 4s expected in the absence of earnings management are missing. We call this pattern "quadrophobia." At first glance, it might appear that this phenomenon faded away at the end of our sample period, but as we show in Section V.C, the number 4 is still significantly underrepresented in pro forma EPS, that is, EPS targeted by financial analysts, even in recent years. In other words, the decline in quadrophobia in GAAP-based EPS over the recent years (observed in Graph D of Figure 1) is at least partly driven by firms switching from rounding up their GAAP-based EPS to rounding up their pro forma EPS.

Note that, by a similar logic, strategic rounding should result in numbers 1–3 also being underrepresented, although to a smaller extent, and numbers 5–9 being overrepresented. Table 1 presents the frequency of each number in the first post-decimal digit of positive EPS data and provides support for this hypothesis. The frequency of numbers 2–5 is statistically significantly below 0.1, whereas

[8]In subsequent tests, to compare the frequency of a number in two different samples, we use the statistic $\tilde{z} = \frac{p_1 - p_2}{\sqrt{p(1-p)\left(\frac{1}{n_1} + \frac{1}{n_2}\right)}}$, where p_1, p_2 are the frequencies of this number in the two samples, n_1, n_2 are the sample sizes, and p is the frequency of this number in the combined sample of size $n_1 + n_2$. Under the hypothesis that the frequency in the two samples is the same, $\tilde{z}$ is a standard Normal variable (Fleiss, Levin, and Paik (2003)).

[9]For the reasons explained in Section II.C, we use the number of shares used to calculate basic EPS pre-1997 and the number of shares used to calculate diluted EPS post-1997. Using Compustat variable names, the unrounded basic (diluted) EPS equals (IBADJQ + XIDOQ) × 100 divided by CSHPRQ (CSHFDQ). For example, if this ratio equals 33.48 cents, the first post-decimal digit is 4.

[10]Firms with negative EPS have an incentive to avoid numbers greater than or equal to 5 in the first post-decimal digit (because rounding would then decrease reported EPS), and to overrepresent numbers smaller or equal to 4. We confirm this pattern for negative EPS data in Table A4 in the Supplementary Material.

TABLE 1

Distribution of the First Post-Decimal Digit in Positive EPS

Table 1 reports the frequency of numbers 0–9 in the first post-decimal digit of quarterly earnings per share (EPS) expressed in cents over the period of 1980 to 2021. EPS is calculated as primary EPS before 1997 and as diluted EPS starting in 1997. The sample includes all firm-quarter observations for which EPS is greater than 0.1 cents. *Z*-statistics for the test of the null hypothesis that the frequency of each digit is equal to 10% are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

0	1	2	3	4	5	6	7	8	9
0.1070***	0.1007*	0.0953***	0.0915***	0.0870***	0.1047***	0.1049***	0.1035***	0.1013***	0.1040***
(19.24)	(1.83)	(−12.92)	(−23.28)	(−35.82)	(12.99)	(13.56)	(9.72)	(3.55)	(11.13)

the frequency of numbers 5–9 is statistically significantly above 0.1. This pattern is consistent with the findings in Craig (1992) and Das and Zhang (2003) for earlier samples.

As is apparent from Table 1, the deviation from the uniform distribution is the largest for the number 4. This is in line with the observation that the amount of discretion needed to round up reported EPS is minimized when the first post-decimal digit is a 4. We therefore focus on the distribution of the number 4 as our key characteristic of interest. Although this allows us construct the simplest possible measure of accounting aggressiveness, our results also hold for measures that account for the distribution of other digits (see Section VII).[10]

In the remainder of this section, we show how firms engaging in strategic rounding have adjusted the EPS measure they target in response to regulatory change.

C. The Effects of FAS 128: Rounding in Basic and Diluted EPS

To accurately measure the incidence of quadrophobia, it is important to distinguish between basic and diluted EPS. Diluted EPS accounts for outstanding stock options, warrants, and convertible securities that can be converted into common stock and that thereby reduce EPS. Prior to adoption of FAS 128 in 1997, firms were required to report *primary* EPS, which included the dilutive effect of certain stock-based awards if such inclusion diluted EPS by at least 3% (the "materiality threshold"). In addition, firms that exceeded the "materiality threshold" were also required to report fully diluted EPS, which included all potentially dilutive securities. In 1997, FAS 128 replaced primary EPS with basic EPS (the number that excludes any potential dilution from the calculation of EPS) and required dual representation of basic and diluted EPS on the income statement for all companies.

Prior to adoption of FAS 128, primary EPS was the main measure relied upon by analysts and other consumers of financial statements because a large percentage of reporting companies did not have to report fully diluted EPS. Indeed, in our sample, fewer than 4% of companies reported fully diluted EPS prior to 1997. In

[10]Firms with negative EPS have an incentive to avoid numbers greater than or equal to 5 in the first post-decimal digit (because rounding would then decrease reported EPS), and to overrepresent numbers smaller or equal to 4. We confirm this pattern for negative EPS data in Table A4 in the Supplementary Material.

contrast, after the adoption of FAS 128, analysts and investors likely shifted their focus to diluted EPS because it is more informative to investors than basic EPS.[11] We confirm this hypothesis by comparing basic and diluted EPS to the IBES variable ACTUAL (i.e., "actual EPS"), which IBES constructs by adjusting the company's reported EPS data to the method used by most analysts: Actual EPS reported by IBES is indeed closer to diluted than to basic EPS. In particular, in the subsample with positive EPS, the median difference between basic (diluted) EPS and actual EPS reported by IBES is 0.47 (−0.12) cents over our sample period.

It is unlikely that managements are able simultaneously to round basic and diluted EPS unless they coincide. Thus, we expect that quadrophobia will be pronounced in primary EPS prior to the adoption of FAS 128 and in diluted EPS thereafter. Graphs A and B of Figure 2 are consistent with this hypothesis. Graph A shows that the frequency of the number 4 in basic EPS is substantially higher than in diluted EPS post-1997, and its frequency in diluted EPS post-1997 is as low as in primary EPS before 1997.[12] Graph B focuses on the post-1997 period and the subsample where the basic and diluted EPS differ from each other by at least 0.1 cents, to ensure that the post-decimal digits in these two EPS numbers are different. For this subsample, we observe very little evidence of rounding in basic EPS and significant evidence of rounding in diluted EPS. This suggests that rounding in basic EPS observed in Graph A is mostly driven by the subsample where basic and diluted EPS coincide.

Overall, the data indicate that FAS 128 caused a shift in rounding from primary to diluted EPS. Therefore, all our analysis (including the results presented above in Figure 1 and Table 1) measures quadrophobia using primary EPS prior to 1997 and diluted EPS starting in 1997.

III. Earnings Management Measure and Persistence

In this section, we introduce our key firm-level measure of rounding behavior and show that quadrophobia is persistent, that is, certain firms are systematically more likely to strategically round up their reported EPS.

For each firm-quarter, we define its quadrophobia score (Q-score) using the extent of its past rounding behavior. In particular, $Q^{(N)}$ is defined based on the previous N quarters: $Q_{i,t}^{(N)}$ for firm i in quarter t is set equal to 0 if there was at least one 4 in the first post-decimal digit of the firm's EPS over N quarters with positive earnings prior to but not including quarter t, and equal to 1 otherwise. Formally, if $d_{i,j}$ denotes the first post-decimal EPS digit for firm i in quarter j, and $1_{d_{i,j}=4}$ is the indicator for whether this digit is a 4,

[11] Some respondents to the EPS Prospectus noted that they did not find basic EPS to be a useful statistic and thought that users would focus only on diluted EPS (see Statement of Financial Accounting Standards No. 128). See also the discussion in Jennings, LeClere, and Thompson (1997).

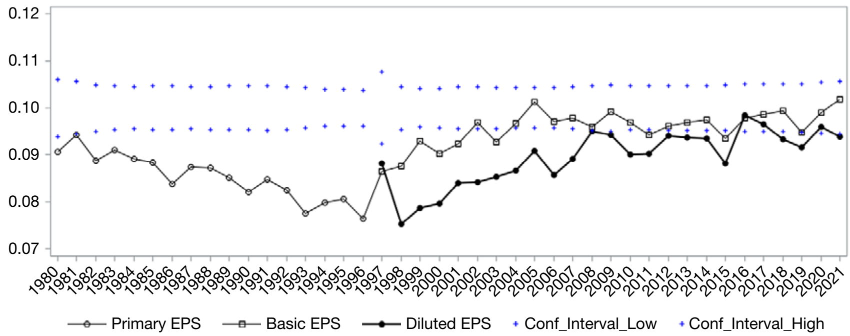
[12] The year 1997 seems to be a transition year, in which firms adjust to the new reporting standards: Basic EPS features less rounding compared with the previous years, and rounding in diluted EPS is not yet as strong either. In addition, not all firms report diluted EPS in 1997, which limits the sample size in 1997, and is the reason why the confidence intervals in Figures 1, 2, and 4 are wider in 1997 than in other years.

FIGURE 2

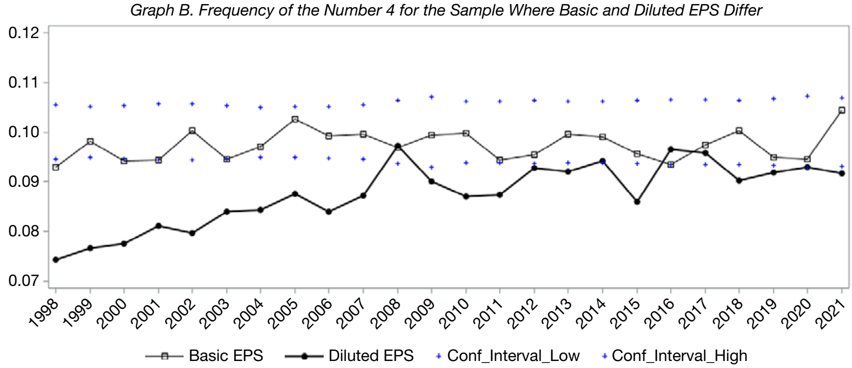
The Adoption of FAS 128: Basic Versus Diluted EPS

Figure 2 explores whether the adoption of FAS 128 in 1997 shifts rounding from basic to diluted EPS. Graph A presents the frequency of the number 4 in the first post-decimal digit of quarterly primary EPS (pre-1997), and basic and diluted EPS (starting in 1997), all expressed in cents. The sample consists of all firm-quarter observations with the corresponding EPS number greater than 0.1 cents. Graph B presents the frequency of the number 4 in basic and diluted EPS post-1997, but only for the subsample where basic and diluted EPS differ by at least 0.1 cents. The blue "plus" marks in both graphs present 95% confidence intervals around 0.1. In Graph A, the confidence interval in 1997 and after is constructed for the sample for which diluted EPS data are available.

Graph A. Frequency of the Number 4 in Primary, Basic, and Diluted EPS



Graph B. Frequency of the Number 4 for the Sample Where Basic and Diluted EPS Differ



(1)
$$Q_{i,t}^{(N)} = \begin{cases} 0, & \text{if } \sum_{j=1}^{N} 1_{d_{i,j}=4} > 0, \\ 1, & \text{if } \sum_{j=1}^{N} 1_{d_{i,j}=4} = 0, \end{cases}$$

where j spans N quarters with positive earnings prior to but not including quarter t. If some of the quarters $t-1,\ldots,t-N$ have negative earnings, we go further back in time, until we get a total of N preceding quarters with positive earnings.[13]

[13]We skip quarters with negative earnings because for those quarters, strategic rounding results in overrepresentation of the number 4 (see footnote 10). If firm i has less than N quarters with positive earnings prior to quarter t, or if we need to skip more than 10 quarters with negative earnings, then we set $Q_{i,t}^{(N)}$ for this firm-quarter as missing, to avoid going back too far in time.

TABLE 2

Persistence of Quadrophobia

Table 2 reports how the probability of observing the number 4 in the first post-decimal digit of earnings per share (EPS) of a given firm depends on the frequency of the number 4 for this firm in the past. For firm-quarter (i,t), the variable $Q_{it}^{(N)}$ is set to 0 if there was at least one 4 in the first post-decimal digit of EPS of firm i over N quarters with positive earnings prior to but not including quarter t, and is set to 1 otherwise. We next divide the sample into two subsamples, based on the value of $Q_{it}^{(N)}$ being equal to either 1 (i.e., quadrophobia in the past) or 0 (i.e., no quadrophobia in the past), and compute (for both of these subsamples) P_{t+k}, which is the frequency of the number 4 among firm-quarter observations with EPS greater than 0.1 cents in quarter $t+k$, for $k=0,1,2,3$. Z-statistics for the test that the difference in the frequency P_{t+k} between the two subsamples is 0 are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

		$N=1$	$N=2$	$N=4$	$N=10$	$N=20$	$N=40$
P_t	$Q_t^{(N)}=1$	0.086	0.085	0.084	0.081	0.076	0.071
	$Q_t^{(N)}=0$	0.093	0.092	0.091	0.090	0.088	0.087
	Z-test	(5.46)***	(6.61)***	(8.91)***	(11.95)***	(11.34)***	(6.70)***
P_{t+1}	$Q_t^{(N)}=1$	0.086	0.085	0.084	0.080	0.076	0.071
	$Q_t^{(N)}=0$	0.092	0.091	0.091	0.090	0.088	0.087
	Z-test	(4.86)***	(5.95)***	(8.20)***	(11.89)***	(10.93)***	(6.42)***
P_{t+2}	$Q_t^{(N)}=1$	0.086	0.085	0.084	0.081	0.077	0.072
	$Q_t^{(N)}=0$	0.090	0.091	0.090	0.090	0.088	0.087
	Z-test	(2.91)***	(5.72)***	(7.01)***	(11.37)***	(9.89)***	(5.89)***
P_{t+3}	$Q_t^{(N)}=1$	0.086	0.085	0.084	0.081	0.077	0.072
	$Q_t^{(N)}=0$	0.092	0.091	0.090	0.090	0.088	0.087
	Z-test	(4.68)***	(6.43)***	(7.41)***	(10.43)***	(9.93)***	(5.95)***

Firms with a Q-score of 1 are more likely to have engaged in quadrophobia compared with those with a Q-score of 0.

We next examine whether quadrophobia is persistent, that is, whether the Q-score is negatively correlated with the frequency of the number 4 in EPS reported by the firm in the future. Table 2 presents this analysis for multiple values of N. We divide our entire sample into two subsamples corresponding to values of $Q_{i,t}^{(N)}$ being 0 and 1, and compare the frequency of the number 4 in the first post-decimal digit of EPS (for positive EPS numbers only) reported in quarter $t+k$ across the two subsamples. The results strongly confirm the persistence hypothesis for multiple values of k: The frequency of the number 4 in the subsample exhibiting past quadrophobia ($Q^{(N)}=1$) is consistently and significantly lower than in the subsample without quadrophobia ($Q^{(N)}=0$).

Higher values of N correspond to a longer past history included in the Q-score. Table 2 reports that the difference in the frequency of the number 4 between the two subsamples increases from approximately 0.7 percentage points for $N=1$, 2, and 4 quarters, to approximately 1.5 percentage points for $N=40$, that is, 10 years. The absence of 4s over a 10-year horizon is relatively unlikely in the absence of strategic rounding: If post-decimal digits are uniformly distributed, the probability of no 4 in 40 quarters is 0.9^{40}, or 1.47%. Accordingly, Table 2 reports that if a firm has for 10 years failed to report a 4 in the first post-decimal digit of its EPS, there is only a 7.1% chance that it will report a 4 in the subsequent quarters. The downside of using a higher N is the decline in sample size because a larger number of past observations with positive EPS are required to construct $Q^{(N)}$. In addition, the management team and corporate governance system that were in place several years ago may be different from those in place today, so using a very long past history may lead to a noisy measure of the current financial reporting culture. In the tests that follow, we use $Q^{(4)}$ as our baseline measure and often call it simply the Q-score, but verify the robustness of all the results to higher values of N.

It is possible that the results in Table 2 merely reflect the stability of EPS data rather than the persistence of strategic rounding behavior. In particular, if the difference in EPS between two subsequent quarters is smaller than 0.1 cents, then the first post-decimal digit in these EPS figures is likely to be the same, leading to a positive autocorrelation in the frequency of the number 4. To address this concern, we search for all pairs of consecutive quarters with the same post-decimal digit of EPS. These observations constitute less than 5% of the sample, and the persistence results remain unchanged after their exclusion. We also use a slightly different approach by excluding observations with a difference in consecutive EPS of less than 0.05 or 0.1 cents and obtain similar results. Thus, the positive correlation is driven by the persistence in rounding behavior and not in the levels of EPS.

Finally, in Table 5, we verify that quadrophobia is persistent after controlling for several key firm characteristics, including firm size, market-to-book ratio, and analyst coverage.

IV. Predicting Accounting Violations

Quadrophobia's persistence suggests that certain management teams are more likely than others to engage in strategic rounding, thereby supporting use of the Q-score to measure the aggressiveness of firms' financial reporting practices. However, whether the Q-score captures relatively benign adjustments, or more serious forms of earnings management, cannot be discerned from Q-scores alone because quadrophobia can result from the exercise of legitimate accounting discretion that violates no accounting standards. In this section, we show that even if this is the case, quadrophobia is practiced by managements that are more likely to engage in serious financial reporting misconduct. Moreover, Q-scores predict accounting violations even after controlling for firm characteristics from the predictive models developed in the literature and also improves the predictive power of these models.

A. Data on Accounting Violations

To capture serious accounting misconduct, we examine the incidence of restatements and SEC enforcement actions. Relying on each of these metrics raises unique advantages and limitations (e.g., Dechow et al. (2011), Karpoff, Koester, Lee, and Martin (2017)). Restatements capture potential misconduct in a more comprehensive manner but reflect intentional as well as unintentional misstatements. The AAER sample represents more direct evidence of wrongful manipulation, but may be subject to selection biases resulting from the exercise of discretion by staff of the SEC's enforcement division in deciding which cases to pursue. We also show that our measure predicts securities class action lawsuits, but since those suffer from most severe scope limitations (Karpoff et al. (2017)), we present this analysis for robustness in Section VII.

The restatement data are from Audit Analytics' Non-Reliance Restatements database and cover restatements filed between Mar. 1995 and Feb. 2020. We only include restatements filed to correct accounting errors and that have an adverse effect on financial statements.[14] We exclude restatements for errors in accounting and clerical applications. We identify all quarters that were restated and, if a firm's annual financial statement was restated, assume that all quarters in that year were restated. The AAER data are obtained from the USC AAER data set developed by Dechow et al. (2011). The data set includes AAER Nos. 1–4012, issued between May 17, 1982 and Dec. 31, 2018. For both restatements and AAERs, we refer to the period when the misstatements occur as the "alleged violation period."

B. Predictive Regressions

We follow the literature (e.g., Beneish (1999), Dechow et al. (2011)) and perform the predictive analysis at the firm-year level in our baseline tests; we show the robustness to firm-quarter level analysis in Section VII. For each type of event (restatements and AAERs), we conduct probit regressions in which the dependent variable for firm-year (i,t) is set to 0 if the firm never experiences this event after year t or if the alleged violation period for this event starts later than 5 years after year t, and set to 1 if the alleged violation period starts within 5 years from year t. Accordingly, we restrict the sample period for the restatement (AAER) tests to start one quarter before the first quarter of restatement (AAER) coverage and to end 5 years before the last quarter of coverage, so that there is full coverage of restatements (AAERs) for the 5 years immediately following the respective firm-year observation.[15]

Our key independent variable is the Q-score, $Q^{(N)}$, as introduced in Section III. For fiscal year t, we use the Q-score measured for the first quarter of year $t+1$, so that it captures the incidence of the number 4 during N quarters ending with the last quarter of year t, aligning it with the timing of other predictive variables.[16] We report the results for $N=4$ in Table 3 and show the robustness of these results to higher values of N in Table 4 and the Supplementary Material.

The results for restatements and AAERs are presented in Panels A and B of Table 3, respectively. Column 1 of Table 3 considers the model that includes the Q-score as the sole explanatory variable. The coefficient for the Q-score is positive and significant at the 1% level in predicting both types of events. In columns 2–6, we examine whether the Q-score retains its predictive power after controlling for other firm characteristics that have been shown to predict accounting violations. In particular, following Price et al. (2011), Larcker and Zakolyukina (2012), and

[14]This sample includes three nonmutually exclusive types of restatements: i) restatements reflecting financial fraud, irregularities, and misrepresentations; ii) restatements due to accounting rule (GAAP/FASB) application failure; and iii) restatements triggered by formal or informal SEC inquiry (e.g., SEC comment letter).

[15]Specifically, our sample period for restatement predictive regressions starts in 1995 (since the Audit Analytics' coverage of the restatement data becomes more comprehensive from 1995 onward) and ends in 2015 (since the last alleged violation quarter for restatements is 2020Q4). Similarly, for AAERs, the last alleged violation quarter is 2016Q4, so our sample period for AAER predictive regressions is from 1980 to 2011.

[16]For $N=4$, the period captured by the Q-score exactly aligns with other variables in our predictive regressions, since both $Q^{(4)}$ and other annual variables are measured over the four quarters of year t, as long as earnings in these quarters are positive. For higher values of N and/or if year t has some quarters with negative earnings, $Q^{(N)}$ also captures several quarters prior to year t.

TABLE 3

Predictive Regressions

Table 3 presents firm-year-level probit regressions, where the dependent variable for firm-year (i, t) is 0 if the firm never experiences an AAER (restatement) after year t or if the alleged violation period for this event starts later than 5 years after year t, and 1 if the alleged violation period starts within 5 years from year t. The sample consists of firm-year observations with available data on the presence or absence of AAERs (restatements) for the next 5 years, as described in Section IV. For firm-year (i, t), Q_SCORE is set to 0 if there was at least one "4" in the first post-decimal digit of earnings per share reported by the firm over four quarters with positive earnings ending with the last quarter of year t, and 0 otherwise. Column 2 includes JONES_RES, defined as the absolute value of discretionary accruals from the modified Jones model (Dechow et al., 1995). Column 3 includes the eight predictors from Beneish's (1999) M-score model, column 4 includes the nine predictors from Dechow et al.'s (2011) F-score model 2, and column 5 combines the M-score and F-score model predictors. Column 6 presents the augmented model, which adds 11 additional predictors from Alawadhi et al. (2020) to the model in column 5. The list of all these predictors and their definitions are in the Appendix. t-Statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Predicting AAERs

	AAER					
	1	2	3	4	5	6
Q_SCORE	0.08***	0.07***	0.08***	0.07***	0.07**	0.11***
	(4.19)	(3.53)	(2.71)	(2.87)	(2.45)	(3.01)
JONES_RES		0.04***				
		(2.81)				
RSST_ACCRUALS			0.47***		0.38***	0.49***
			(5.22)		(3.76)	(3.69)
CHANGE_IN_RECEIVABLES			0.76***		0.72***	0.26
			(4.07)		(3.47)	(0.94)
CHANGE_IN_INVENTORY			0.38		0.38	0.62*
			(1.59)		(1.47)	(1.91)
PERCENT_SOFT_ASSETS			0.59***		0.58***	0.71***
			(10.42)		(9.67)	(7.71)
CHANGE_IN_CASH_SALES			0.11***		0.06**	0.02
			(6.13)		(2.44)	(0.64)
CHANGE_IN_ROA			−0.20*		−0.18	−0.10
			(−1.79)		(−1.39)	(−0.51)
SECURITY_ISSUE_FLAG			0.39***		0.39***	0.44***
			(6.25)		(5.99)	(5.10)
ABNORMAL_CHANGE_IN_EMPLOYEES			−0.04		−0.04	0.04
			(−1.00)		(−0.88)	(0.67)
OPERATING_LEASES_FLAG			0.23***		0.22***	0.20***
			(9.28)		(8.41)	(5.83)
DAYS_SALES_IN_RECEIVABLES				0.05*	0.05	0.06
				(1.94)	(1.42)	(1.22)
GROSS_MARGIN_INDEX				0.02	0.00	0.02
				(1.35)	(0.20)	(0.55)
ASSET_QUALITY_INDEX				0.02	0.02	0.03
				(1.64)	(1.60)	(1.48)
SALES_GROWTH_INDEX				0.23***	0.11***	0.13***
				(12.07)	(3.15)	(2.67)
DEPRECIATION_INDEX				0.04	−0.01	−0.02
				(1.00)	(−0.26)	(−0.29)
SG&A_INDEX				0.07	0.09	0.08
				(1.41)	(1.19)	(0.82)
LEVERAGE_INDEX				0.02	−0.02	−0.00
				(0.72)	(−0.51)	(−0.04)
TOTAL_ACCRUALS_TO_TOTAL_ASSETS_RATIO				0.45***	−0.05	−0.05
				(5.28)	(−0.51)	(−0.37)
Constant	−2.23***	−2.22***	−3.05***	−2.66***	−3.29***	−3.64***
	(−138.46)	(−122.20)	(−41.77)	(−32.59)	(−25.37)	(−19.02)
Additional predictors for augmented model	No	No	No	No	No	Yes
No. of obs.	151,566	119,571	66,704	81,506	60,510	43,748

(continued on next page)

TABLE 3 (continued)

Predictive Regressions

Panel B. Predicting Restatements

	Restatement					
	1	2	3	4	5	6
Q_SCORE	0.04***	0.04***	0.04***	0.04***	0.05***	0.05***
	(3.63)	(3.24)	(2.98)	(2.80)	(3.47)	(2.63)
JONES_RES		0.03***				
		(3.21)				
RSST_ACCRUALS			0.09*		0.06	0.17**
			(1.78)		(1.08)	(2.39)
CHANGE_IN_RECEIVABLES			−0.04		−0.24*	−0.19
			(−0.30)		(−1.67)	(−1.06)
CHANGE_IN_INVENTORY			−0.16		−0.25	−0.23
			(−1.03)		(−1.49)	(−1.17)
PERCENT_SOFT_ASSETS			0.19***		0.23***	0.04
			(6.40)		(7.16)	(0.98)
CHANGE_IN_CASH_SALES			0.02*		−0.01	0.01
			(1.70)		(−0.59)	(0.15)
CHANGE_IN_ROA			−0.08		−0.03	−0.02
			(−1.34)		(−0.38)	(−0.26)
SECURITY_ISSUE_FLAG			0.11***		0.12***	0.08***
			(4.39)		(4.48)	(2.73)
ABNORMAL_CHANGE_IN_EMPLOYEES			−0.02		0.01	0.01
			(−0.72)		(0.34)	(0.41)
OPERATING_LEASES_FLAG			0.15***		0.15***	0.18***
			(11.00)		(10.98)	(10.26)
DAYS_SALES_IN_RECEIVABLES				0.03**	0.06***	0.05*
				(1.97)	(3.09)	(1.69)
GROSS_MARGIN_INDEX				0.01	0.01	0.02
				(0.39)	(0.60)	(0.83)
ASSET_QUALITY_INDEX				−0.01	−0.01	−0.00
				(−0.90)	(−0.79)	(−0.24)
SALES_GROWTH_INDEX				0.09***	0.14***	0.10**
				(5.16)	(4.50)	(2.25)
DEPRECIATION_INDEX				0.01	0.01	0.00
				(0.58)	(0.18)	(0.03)
SG&A_INDEX				0.08***	0.10**	0.03
				(2.62)	(2.48)	(0.54)
LEVERAGE_INDEX				0.01	0.01	−0.01
				(0.34)	(0.34)	(−0.41)
TOTAL_ACCRUALS_TO_TOTAL_ASSETS_RATIO				−0.02	−0.06	0.06
				(−0.36)	(−0.87)	(0.82)
Constant	−0.99***	−0.95***	−1.21***	−1.17***	−1.60***	−1.28***
	(−113.04)	(−92.99)	(−39.99)	(−21.46)	(−20.76)	(−12.25)
Additional predictors for augmented model	No	No	No	No	No	Yes
No. of obs.	101,573	76,285	50,181	53,689	45,090	33,126

Alawadhi et al. (2020), we analyze a set of predictive variables identified by several prominent benchmark models developed in the literature. First, we add discretionary accruals, one of the most common measures of accounting quality. Specifically, in column 2, we use the absolute value of discretionary accruals from the modified Jones model (Dechow et al. (1995)), and we discuss the robustness of this analysis to using performance-matched discretionary accruals (Kothari et al. (2005)) in Section VII. Next, in columns 3 and 4, respectively, we consider the eight predictors used by Beneish (1999) to develop the M-score and the nine predictors from model 2 used by Dechow et al. (2011) to develop the F-score. In column 5, we present the

TABLE 4

Performance of the Predictive Model With and Without the Q-Score

Panels A and B of Table 4 present the ROC analysis for AAERs (Panel A) and restatements (Panel B): We calculate the AUCs for predictive probit models without and with the Q-score and report them in the first and second rows of each panel, respectively. The third row presents the increase in AUC due to the addition of the Q-score, and the fourth row presents the corresponding p-value based on DeLong, DeLong, and Clarke-Pearson (1988). The dependent variable for firm-year (i, t) is an indicator set to 1 if the alleged violation starts within 5 years from year t, that is, between quarter 1 of year $t+1$ and quarter 4 of year $t+5$. The model in the first 4 columns in both panels ("M-score + F-score") combines the eight predictors from Beneish's (1999) M-score model and the nine predictors from Dechow et al.'s (2011) F-score model 2; it is the analog of column 5 in Table 3. The difference between these 4 columns is the definition of the Q-score: We consider $Q^{(4)}$, $Q^{(10)}$, $Q^{(20)}$, and $Q^{(40)}$, as defined in Section III. Columns 5–8 in both panels ("Augmented Model") augment the models in columns 1–4 (i.e., the 17 variables from the M-score and F-score models combined) with 11 additional predictive variables from Alawadhi et al. (2020); it is the analog of column 6 in Table 3. The list and definitions of all these variables are in the Appendix. Panel C presents the classification table for the augmented model in columns 5–8 in Panels A and B, that is, the model that combines the Q-score with 28 predictive variables from Beneish (1999), Dechow et al. (2011), and Alawadhi et al. (2020). It reports the number of true positives (TP), true negatives (TN), false positives (FP), false negatives (FN), accuracy (Acc.), sensitivity (Sens.), specificity (Spec.), and precision (Prec.) for the probability cutoff that maximizes the simple average of sensitivity and specificity.

	M-Score + F-Score				Augmented Model			
	$Q^{(4)}$	$Q^{(10)}$	$Q^{(20)}$	$Q^{(40)}$	$Q^{(4)}$	$Q^{(10)}$	$Q^{(20)}$	$Q^{(40)}$
Panel A. Predicting AAERs								
AUC without Q-score	0.677	0.679	0.685	0.680	0.690	0.694	0.695	0.687
AUC with Q-score	0.682	0.690	0.694	0.688	0.700	0.711	0.723	0.723
Difference in AUC	0.005	0.010	0.009	0.007	0.010	0.017	0.028	0.036
p-Value	0.002	0.000	0.001	0.114	0.000	0.000	0.000	0.000
No. of obs.	60,510	54,624	42,231	24,788	43,748	40,151	31,887	19,741
Panel B. Predicting Restatements								
AUC without Q-score	0.554	0.554	0.557	0.562	0.576	0.576	0.586	0.599
AUC with Q-score	0.557	0.557	0.558	0.565	0.578	0.579	0.589	0.602
Difference in AUC	0.003	0.003	0.002	0.003	0.003	0.003	0.003	0.003
p-Value	0.007	0.005	0.085	0.103	0.006	0.008	0.012	0.086
No. of obs.	45,090	41,121	32,511	20,999	33,126	30,807	25,137	17,065

Panel C. Model Quality Measures for the Augmented Model

	No. of Obs.	TP	TN	FP	FN	Acc.	Sens.	Spec.	Prec.
AAERs with $Q^{(4)}$	43,748	391	30,312	12,780	265	0.70	0.60	0.70	0.03
AAERs with $Q^{(10)}$	40,151	388	26,804	12,736	223	0.68	0.64	0.68	0.03
AAERs with $Q^{(20)}$	31,887	301	20,719	10,721	146	0.66	0.67	0.66	0.03
AAERs with $Q^{(40)}$	19,741	146	14,476	5,000	119	0.74	0.55	0.74	0.03
Restatements with $Q^{(4)}$	33,126	3,304	15,562	11,361	2,899	0.57	0.53	0.58	0.23
Restatements with $Q^{(10)}$	30,807	3,115	14,383	10,611	2,698	0.57	0.54	0.58	0.23
Restatements with $Q^{(20)}$	25,137	3,111	9,547	10,894	1,585	0.50	0.66	0.47	0.22
Restatements with $Q^{(40)}$	17,065	1,772	8,134	5,752	1,407	0.58	0.56	0.59	0.24

model that combines all the 17 variables from the M-score and F-score models. Finally, in column 6, we consider the most comprehensive model (which we call the "augmented model"), in which we augment the model in column 5 with 11 additional variables explored by Alawadhi et al. (2020): common financial ratios and firm-level controls (market capitalization, market-to-book ratio, leverage, profit margin, return on assets, basic earnings power, inventory turnover, and the ratio of intangibles to total assets) and three variables related to financial distress (Altman's Z-score, financial distress indicator, and the indicator for negative earnings). The list and definitions of all the variables included in each model are presented in the Appendix.

The analysis reveals that across all these specifications, the coefficient for the Q-score retains its strong significance and slightly increases in magnitude as we include additional predictive variables. Table A7 in the Supplementary Material shows the robustness of these results for $Q^{(10)}$.

C. Receiver Operating Characteristic Analysis

To further explore the Q-score's predictive power, we perform the ROC analysis, which evaluates the model's joint ability to correctly detect both "positives" (i.e., instances of accounting violations) and "negatives" (i.e., instances without violations). This methodology is a common diagnostic tool to assess the performance of predictive models (e.g., Larcker and Zakolyukina (2012), Alawadhi et al. (2020), and Bertomeu et al. (2021)).

Specifically, for any predictive model, such as those in Table 3, and any given probability cutoff, we classify firm-years with fitted values above (below) this cutoff as model-predicted positives (negatives), and compare those with the actual positives (negatives) in the data as measured by the dependent variable in that model.[17] This classifies all firm-year observations into four categories: True and false positives (TP and FP) are observations for which the fitted value from the model is above the cutoff, and the dependent variable is equal to 1 and 0, respectively, whereas true and false negatives (TN and FN) are observations for which the fitted value is below the cutoff, and the dependent variable is equal to 0 and 1, respectively. The model's true positive rate (called "sensitivity") is defined as $\frac{\text{TP}}{\text{TP+FN}}$ and captures the rate of correctly classified instances of misreporting. Similarly, the model's true negative rate (called "specificity") is defined as $\frac{\text{TN}}{\text{TN+FP}}$ and captures the rate of correctly classified instances where misreporting does not occur. Increasing the probability cutoff reduces false positives and improves model specificity, but at the expense of decreasing model sensitivity, and vice versa. The ROC analysis explicitly recognizes this trade-off by plotting the model's sensitivity as a function of $(1 - \text{specificity})$ for all possible cutoffs. The area under the ROC curve (AUC) is used to assess the overall predictive ability of the model.

In Figure 3 and Table 4, we use the ROC methodology to analyze how the addition of the Q-score can improve the predictive power of existing models. Our baseline specification includes the 17 variables from Beneish's (1999) M-score and Dechow et al.'s (2011) F-score models combined, with and without the Q-score, which corresponds to model 5 of Table 3. The first 4 columns in Panel A of Table 4 report that for AAERs, the addition of $Q^{(4)}$ to the M-score + F-score model increases the AUC by 0.5 percentage points. Using the nonparametric approach of DeLong, DeLong, and Clarke-Pearson (1988), we confirm that the improvement in AUC is significant at the 1% level. As we move from $Q^{(4)}$ to $Q^{(10)}$, $Q^{(20)}$, and $Q^{(40)}$, the improvements in the AUC slightly increase in magnitude, although the sample size gradually drops because the Q-score is not defined for a larger number of observations.[18]

Alawadhi et al. (2020) point out that a model does well at discriminating between misreporting and accurate reporting if its AUC is at least 0.7. Although the AUCs for the M-score + F-score model are slightly lower than 0.7, we obtain AUCs

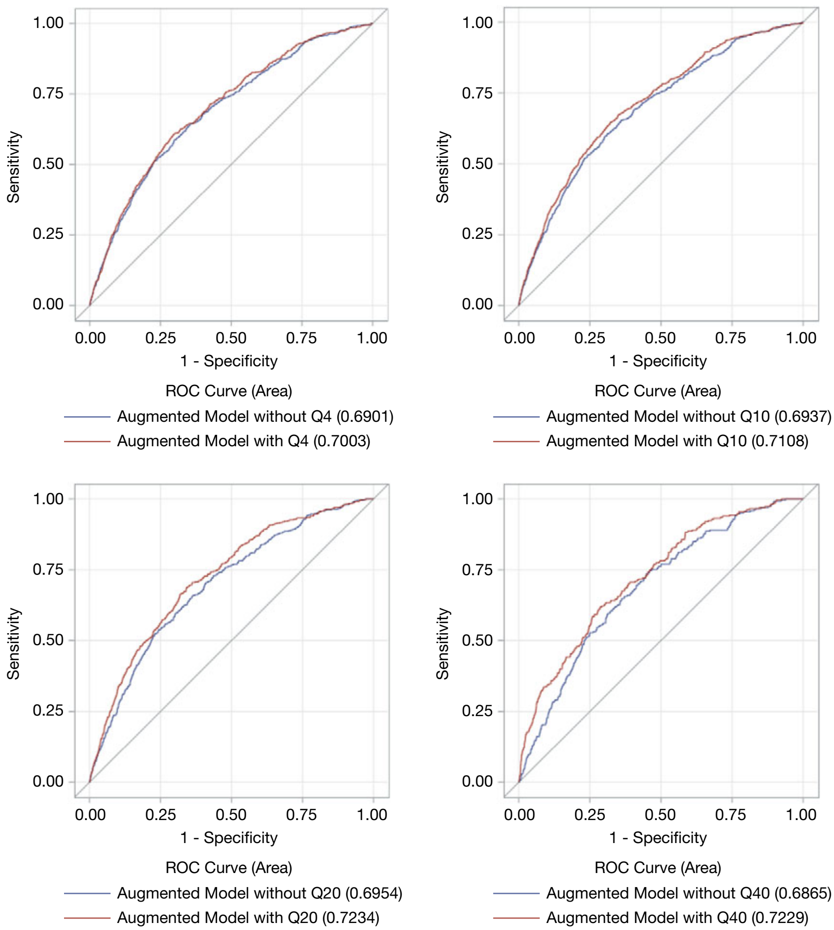
[17] In particular, as in Table 3, the dependent variable for firm-year (i,t) is an indicator variable set to 1 if the alleged violation occurs within the next 5 years. We obtain similar results if we shorten the time window for observing a violation to the next 1 year, 2 years, and 3 years.

[18] The AUC for the model without the Q-score changes across columns because we adjust the sample to ensure that the AUCs with and without the Q-score for each column are calculated based on the same sample.

FIGURE 3

ROC Curves for Models Predicting AAERs With and Without the Q-Score

Figure 3 presents the ROC curves for predicting AAERs, that is, the plots of the true positive rate (sensitivity) as a function of the false positive rate (1 − specificity) for various probability threshold levels. The dependent variable for a firm-year (i, t) is an indicator set to 1 if the alleged violation occurs in the period $[t, t+5]$. The explanatory variables correspond to the augmented model in column 6 of Table 3, which combines the 8 predictors from Beneish's (1999) M-score model, the 9 predictors from Dechow et al.'s (2011) F-score model 2, and 11 additional predictors from Alawadhi et al. (2020), both with and without the Q-score as an additional predictor. The list and definitions of all these variables are in the Appendix. The only difference between the 4 graphs of this figure is the definition of the Q-score: We consider $Q^{(4)}$, $Q^{(10)}$, $Q^{(20)}$, and $Q^{(40)}$, as defined in Section III. "ROC Curve (Area)" reports the area under the curve (AUC) for each model, both without the Q-score (area under the blue curve) and with the Q-score (area under the red curve).



above 0.7 if we augment this model with additional predictive variables. Specifically, in columns 5–8 of Table 4, we present the ROC analysis for model 6 of Table 3, that is, the F-score + M-score model augmented with the 11 predictors from Alawadhi et al. (2020). The augmented model without the Q-score features AUCs slightly below 0.7, but the addition of the Q-scores now increases the AUC more substantially, by 2–4 percentage points (e.g., from 0.687 to 0.723 for $Q^{(40)}$). As a result, the AUC of the model with the Q-score is above 0.7 for all definitions of the Q-score. Figure 3 illustrates these findings and shows that the ROC curves for

the models without Q-scores lie strictly below the corresponding ROC curves for the models that add Q-scores.

Panel B of Table 4 reports that for restatements, the addition of the Q-score also significantly increases the AUC across most specifications, although the increase has a smaller magnitude. However, the AUCs are lower than those for AAERs and stay below 0.7 even upon the inclusion of additional predictors from the augmented model. The model's lower predictive ability for restatements might reflect the fact that many restatements are errors, rather than material irregularities (e.g., Dechow et al. (2011), Karpoff et al. (2017)) and is consistent with other papers in the literature.[19]

We conclude this analysis by calculating several performance measures of the predictive model with the Q-score. We pick the "augmented model" (corresponding to columns 5–8 in Panels A and B of Table 4), and the probability cutoff that maximizes the simple average of sensitivity and specificity. As Alawadhi et al. (2020) discuss, this cutoff is optimal if it is equally costly to label a misreporting firm as non-misreporting and to label a non-misreporting firm as misreporting. Panel C of Table 4 documents the number of true and false positives and negatives, and the key performance measures used in predictive studies: sensitivity, specificity, accuracy $\left(\text{the overall rate of correctly classified instances, i.e., } \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}}\right)$, and precision (the rate of correctly classified positives among all instances classified as positive, i.e., $\frac{\text{TP}}{\text{TP+FP}}$).

For both AAERs and restatements, the model's accuracy and specificity are the highest for $Q^{(40)}$, whereas sensitivity is the highest for $Q^{(20)}$. For example, for AAERs, the augmented model with $Q^{(20)}$ correctly predicts 67% of violations and 66% of nonviolations, and its overall accuracy is 66%. The precision is 3%, which can be thought of as the probability of being caught by the SEC conditional on a violation having occurred. The model for restatements has a lower accuracy, specificity, and sensitivity than for AAERs, in line with its overall poorer performance discussed above.

Overall, the analysis in this section suggests that the Q-score is a simple measure that can be used both as a stand-alone tool and in combination with other firm characteristics to predict serious violations of accounting standards. Thus, even if rounding behavior is benign on its own, it signals an overall aggressive approach to financial reporting.

D. SEC's EPS Initiative

The predictive power of the Q-score highlighted in our article has attracted the interest of practitioners, regulators, and media. On Sept. 28, 2020, the SEC settled two actions described as "the first arising from investigations generated by the Division of Enforcement's EPS Initiative, which utilizes risk-based data analytics to uncover potential accounting and disclosure violations caused by, among other things, earnings management practices."[20] According to the *Wall*

[19]For example, Larcker and Zakolyukina (2012) report an AUC of 63.0 for AAERs but AUCs between 56.6 and 59.7 for restatements (see their Table 5). See also the discussion in Section 5.2 of Bertomeu et al. (2021).

[20]See SEC press release 2020-226 at https://www.sec.gov/news/press-release/2020-226 and AAER Nos. 4174 and 4175.

Street Journal (WSJ), the EPS "initiative's database was built on the basis of" our quadrophobia research, which was "widely read within the SEC."[21] A major international law firm referred to the WSJ article noting that the Commission had "keyed into a trend identified in the academic literature of statistical anomalies in disclosed EPS figures."[22]

One defendant in the 2020 settlement made "adjustments … when … internal forecasts indicated that the company would likely fall short of analyst consensus EPS estimates"; the other "belatedly reversed [a] valuation allowance, increasing its EPS by a penny in a quarter when it otherwise would have fallen short of consensus estimates" (SEC press release 2020-226).

On Aug. 24, 2021, the SEC settled its third action, highlighting that the defendant "reported EPS that met analyst estimates for multiple quarters as a result of accounting violations," and on Apr. 18, 2022, it announced "the fourth action and the highest penalty to date against an issuer in connection with the Division of Enforcement's highly successful and continuing EPS Initiative."[23] According to the WSJ's article referenced above, these settlements are likely not the last, as the SEC is currently "investigating multiple companies over potential manipulations of EPS as part of the ongoing initiative, which may result in charges" (WSJ, Oct. 10, 2021).

All 4 firms that have settled with the SEC rank highly based on their Q-scores. For example, if we sort firms based on the sum of their 10-quarter Q-scores over the sample period, all 4 rank in the top 1% out of more than 15,000 firms with nonmissing Q-scores in our sample. These four enforcement actions are thus consistent with the SEC's application of Q-scores to identify federal securities law violations. To the best of our knowledge, they appear to be the first reported instance of the SEC applying statistical techniques developed in the academic literature to identify such violations.

V. Costs and Benefits of Strategic Rounding

Our results so far suggest that the Q-score can be a useful tool to identify firms with aggressive accounting practices. However, whether strategic rounding is economically important on its own remains an open question. To establish the economic importance of strategic rounding, we follow Burgstahler and Chuk (2017), who propose a framework to evaluate the body of evidence on discontinuities in the distribution of earnings in light of economic theory. Specifically, Burgstahler and Chuk (2017) highlight four characteristics of discontinuity evidence consistent with the theory of earnings management, suggesting that firms manage earnings when the benefits of doing so exceed the costs (pp. 727

[21]See, respectively, "SEC Digs Deeper into Companies' EPS Manipulation" (WSJ, Oct. 10, 2021) and "SEC Probes Whether Companies Rounded Up Earnings Per Share" (WSJ, June 22, 2018).

[22]Latham & Watkins Client Alert: SEC Announces First "EPS Initiative" Enforcement Actions (Oct. 14, 2020), at https://www.lw.com/thoughtLeadership/sec-announces-first-eps-initiative-enforcement-actions.

[23]See SEC press releases 2021-162 and 2022-64 at https://www.sec.gov/news/press-release/2021-162 and https://www.sec.gov/news/press-release/2022-64, and AAER Nos. 4244 and 4294, respectively.

and 744–745). Adapting these four characteristics to our setting, we summarize them as follows:

- The distribution of the first post-decimal digit of EPS deviates from uniform distribution.
- The strength of deviation from the uniform distribution covaries with the strength of incentives created by the costs and benefits of managing earnings.
- The deviation is observed in earnings measures that are widely used in stakeholder decisions.
- It is not observed in earnings measures that are not widely used in stakeholder decisions.

The evidence in Figure 1 and Table 1 is consistent with the first characteristic, and the distinction between basic and diluted EPS discussed in Section II.C is consistent with the third and fourth characteristics. In this section, we establish the second characteristic by studying several costs and benefits of strategic rounding, including the benefits from meeting analyst expectations, increasing executive compensation, and strengthening the firm's bargaining power with creditors. In addition, we provide further support for the third and fourth characteristics by distinguishing between pro forma and GAAP EPS.

A. Basic Determinants of Strategic Rounding

To show that strategic rounding responds to economic incentives, we start by analyzing several basic firm characteristics that affect firms' costs and benefits of rounding up their reported EPS. First, rounding should be more beneficial when the magnitude of EPS is small because a 1-cent increase in EPS then constitutes a larger percentage of the reported number. Second, the benefits of rounding are likely to be higher for firms that face more pressure from public markets. We therefore study the role of analyst coverage and market-to-book ratios: Analyst coverage may incentivize firms to round up in order to meet analyst expectations and, if firms with higher market-to-book ratios have more growth opportunities, they may have more interest in raising capital and thus face more pressure to report higher earnings. The effect of firm size is ambiguous: On the one hand, larger firms may have more following in the market and hence a higher benefit from rounding up, but on the other hand, larger firms may also have higher costs of rounding since they are more intensely scrutinized by auditors and regulators.

We run probit regressions at the firm-quarter level, where the dependent variable (which we call DUMMY4) is an indicator set to 1 if the first post-decimal digit of EPS in that quarter is 4, and 0 otherwise. A negative coefficient on an explanatory variable implies that 4s are less common, that is, quadrophobia is more pronounced as the explanatory variable increases. The sample is restricted to observations with EPS exceeding 0.1 cents.

The results are presented in columns 1 and 2 of Table 5. They are consistent with the hypothesis that quadrophobia is more pronounced when the net benefits of rounding are larger, that is, the magnitude of EPS is smaller, market-to-book ratio is higher, and the firm is covered by analysts. Firm size is on average negatively related to quadrophobia, suggesting that the costs associated with higher scrutiny

TABLE 5

Costs and Benefits of Strategic Rounding

Table 5 presents the results of firm-quarter-level probit regressions of DUMMY4 on company characteristics. DUMMY4 equals 1 if 4 is the first post-decimal digit in earnings per share (EPS) reported in cents in that quarter, and equals 0 otherwise. The sample consists of firm-quarter observations with EPS greater than 0.1 cents. SIZE is the logarithm of total assets, M/B is the ratio of the market value of total assets to the book value of total assets, and EPS is the earnings per share. Each of these variables is winsorized at 1% and 99%. INCENTIVE_RATIO is the sensitivity of the CEO's equity portfolio to changes in the stock price, scaled by total cash compensation and measured for the previous fiscal year, and is defined by equation (2). SC_VEGA is the sensitivity of the CEO's equity portfolio to changes in stock return volatility, scaled by total cash compensation and measured for the previous fiscal year, which is constructed using the method in Core and Guay (2002) and is defined by equation (A.4) in the Supplementary Material. The indicator variable ANALYST is set to 1 if the consensus analyst forecast is available for the corresponding firm-quarter observation, and to 0 otherwise. Q_SCORE for firm *i* in quarter *t* is $Q_{i,t}^{(4)}$, as defined by equation (1). The sample in columns 3–5 is restricted to firms for which managerial stock and option holdings data are available in ExecuComp. The sample in columns 6 and 7 is restricted to firms that were covered by analysts at least once during our sample period. The indicator variable BEFORE_COV (AFTER_COV) is defined for this subsample and equals 1 if the firm-quarter belongs to the period before analyst coverage is initiated for the firm (after all analysts drop coverage). *t*-Statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	DUMMY4						
	Basic Determinants		Equity Incentives			Analyst Coverage	
	1	2	3	4	5	6	7
INCENTIVE_RATIO			−0.03**	−0.03**	−0.04**		
			(−2.08)	(−2.19)	(−2.02)		
SC_VEGA					0.02		
					(0.44)		
SIZE	0.00***	0.00***	0.01***	0.01***	0.01***	0.01***	0.01***
	(2.99)	(3.64)	(4.57)	(4.64)	(4.51)	(4.10)	(4.70)
M/B	−0.01***	−0.01***	−0.00	−0.00	−0.01	−0.01***	−0.01***
	(−3.59)	(−2.99)	(−1.10)	(−1.01)	(−1.36)	(−3.87)	(−3.01)
EPS	0.02***	0.02***	0.02***	0.02***	0.03***	0.03***	0.03***
	(5.72)	(5.73)	(3.48)	(3.44)	(3.73)	(5.93)	(5.88)
ANALYST	−0.08***	−0.08***	−0.07***	−0.07***	−0.07***		
	(−14.32)	(−13.28)	(−3.65)	(−3.59)	(−3.27)		
BEFORE_COV						0.07***	0.07***
						(8.12)	(6.94)
AFTER_COV						0.07***	0.07***
						(7.62)	(7.67)
Q_SCORE		−0.04***		−0.04***	−0.04***		−0.04***
		(−7.54)		(−4.38)	(−4.08)		(−7.56)
Constant	−1.36***	−1.34***	−1.40***	−1.37***	−1.38***	−1.46***	−1.43***
	(−68.32)	(−65.26)	(−33.91)	(−32.48)	(−30.94)	(−56.05)	(−53.15)
No. of obs.	628,223	573,375	151,612	150,336	143,555	525,215	489,685
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

may discourage larger firms from rounding up too aggressively.[24] In column 2, we also include the firm's current Q-score. Its inclusion does not change the coefficients on other firm characteristics, but the Q-score itself has a negative and significant coefficient, in line with the earlier established conclusion that quadrophobia is persistent (Table 2).

B. Executives' Equity Incentives

To further explore whether the prevalence of quadrophobia covaries with the net benefits of rounding up EPS, we study the role of executive compensation. A large literature has examined whether stock-based compensation and holdings

[24]If we include both a linear and a quadratic term of firm size, we observe a nonmonotonic relationship, with the largest and smallest firms being less likely to engage in rounding than medium-sized firms, in line with the costs and benefits discussed above.

provide managers with incentives to manipulate accounting numbers and engage in fraud, based on the notion that misreporting may increase the stock price, thereby increasing the value of the manager's equity portfolio. However, the empirical evidence has been mixed. A number of studies find that the stock price sensitivity of CEO wealth or compensation has a positive association with earnings manipulation, as measured by accruals or the likelihood of restatements and AAERs.[25] At the same time, several influential studies find no evidence of a positive association and hypothesize that equity incentives could instead align managers' interests with those of shareholders.[26] Given these inconclusive results, it is useful to study quadrophobia as a measure of earnings management, as it is distinct from other measures used in the literature.

We therefore examine whether quadrophobia is more pronounced if the CEO's potential total compensation is more closely tied to the stock price. Managerial stock and option holdings data are obtained from ExecuComp. To measure the power of CEO equity-based incentives, we follow Bergstresser and Philippon (2006), who analyze the share of a CEO's total compensation that would come from a 1 percentage point increase in the value of the firm's stock. Bergstresser and Philippon (2006) call this variable INCENTIVE_RATIO and define it as

$$(2) \qquad \text{INCENTIVE\_RATIO}_{i,t} = \frac{\text{ONEPCT}_{i,t}}{\text{ONEPCT}_{i,t} + \text{SALARY}_{i,t} + \text{BONUS}_{i,t}},$$

where the variable ONEPCT captures the dollar change in the value of the CEO's firm-based equity wealth that would come from a 1 percentage point increase in the share price:

$$(3) \qquad \text{ONEPCT}_{i,t} = 0.01 \times \text{PRICE}_{i,t} \times (\text{SHARES}_{i,t} + \text{OPTIONS}_{i,t}),$$

where $\text{PRICE}_{i,t}$ is the share price at the end of year t, and $\text{SHARES}_{i,t}$ ($\text{OPTIONS}_{i,t}$) is the number of shares (options) held by the CEO as reported in the proxy statement of year t.

We follow Bergstresser and Philippon (2006) and analyze INCENTIVE_RATIO measured for the previous fiscal year as our key explanatory variable (we consider several other measures of equity incentives in Section A.3 of the Supplementary Material). In particular, we augment the models in columns 1 and 2 of Table 5 with lagged INCENTIVE_RATIO and present the results in columns 3 and 4 (the sample size drops because many firm-years in our main sample are not in ExecuComp). There is a negative and statistically significant association between the CEO's equity incentives and the likelihood of observing a 4 in the first post-decimal EPS digit. This relationship is robust to controlling for year fixed effects

[25]For example, Bergstresser and Philippon (2006), Burns and Kedia (2006), Efendi, Srivastava, and Swanson (2007), Cornett, Marcus, and Tehranian (2008), and Johnson, Ryan, and Tian (2009). Coles, Hertzel, and Kalpathy (2006) document earnings management prior to the reissuance of executive stock options.

[26]For example, Erickson et al. (2006), Larcker, Richardson, and Tuna (2007), Armstrong et al. (2010), and Jiang, Petroni, and Wang (2010). See Armstrong et al. (2010) for a detailed discussion of the conflicting evidence in this literature.

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and the company's Q-score. Hence, the data are consistent with the hypothesis that managers opportunistically use strategic rounding to inflate their compensation.

Armstrong, Larcker, Ormazabal, and Taylor (2013) point out that theoretically, the stock price sensitivity of executive compensation does not necessarily have a positive effect on the manager's incentives to misreport. Even though it increases the benefits of inflating the stock price by misreporting, it can also have a second, negative effect: If misreporting increases equity risk, then more stock price-sensitive compensation amplifies the effect of higher equity risk on the overall riskiness of the manager's portfolio. This effect may discourage risk-averse managers from misreporting, which in turn can explain the conflicting evidence in the literature. For that reason, Armstrong et al. (2013) suggest controlling for portfolio vega (i.e., the sensitivity of the manager's equity portfolio to stock return volatility) when studying the incentive effects of executive compensation on the decision to misreport. We therefore add a control for the CEO's portfolio vega in column 5 of Table 5.[27] We find that the effect of vega is statistically insignificant, and its addition to the regression does not change the magnitude or significance of the coefficient on INCENTIVE_RATIO. Furthermore, in Section A.3 of the Supplementary Material, we show that vega is not significantly related to the incidence of quadrophobia even if considered separately. These results differ from those of Armstrong et al. (2013), who find that vega is strongly positively related to misreporting and that the effect of vega subsumes the effect of portfolio sensitivity to the stock price when both are included in the regressions.

The different conclusions likely stem from different measures of misreporting used in the two papers: Armstrong et al. (2013) measure misreporting using discretionary accruals and the incidence of AAERs and restatements relating to fraud, misrepresentation, or an investigation by regulators. In contrast to serious accounting violations that lead to restatements and AAERs or require large adjustments to accruals, quadrophobia has relatively low costs, since it only involves inflating EPS by a 10th of a cent and can be implemented by exercising relatively little, potentially legitimate accounting discretion (see also Section VIII). As a result, strategic rounding is less likely to strongly increase equity risk compared with restatements and AAERs, so the role of vega is less important. Moreover, because of the relatively smaller increase in equity risk, the positive effect of equity incentives on misreporting is likely to dominate the negative effect. This can explain why the strength of equity incentives is strongly related to the incidence of quadrophobia, whereas the evidence on its relationship to other measures of earnings management is mixed. We discuss this and other implications of our measure for this line of research in Section VI.

C. Incentives to Meet Analyst Expectations

As established in Table 5, quadrophobia is more pronounced among firms covered by analysts. In particular, if we divide all firm-quarter observations in our

[27]As in Armstrong et al. (2013), we use the method of Core and Guay (2002) to construct two measures of vega: one unscaled and one scaled by total cash compensation. The exact definitions are in Section A.3 of the Supplementary Material. For brevity, we only report the results for scaled vega in Table 5 and show robustness to using unscaled vega in Table A5 in the Supplementary Material.

sample into those with and without analyst coverage, the frequency of the number 4 is 8.2% if a firm has analyst coverage compared with 9.2% if it does not. This suggests that an important benefit of rounding could come from meeting analyst expectations, the hypothesis we explore in more depth in this section.

1. The Pro Forma Effect

Prior literature has shown that the stock market punishes firms for missing analyst earnings expectations and rewards them for beating these expectations (e.g., Bhojraj, Hribar, Picconi, and McInnis (2009)). Analysts tend to issue forecasts based on recurring income, excluding one-time gains and losses, and the resulting EPS figure is called pro forma or "street" EPS. If quadrophobia is driven by the desire to meet analyst expectations, firms should target pro forma rather than GAAP EPS when rounding up their earnings. This section presents evidence supporting this hypothesis.

To identify pro forma EPS, we use the IBES data item ACTUAL, which is constructed by IBES by adjusting reported EPS data to the method used by the majority of analysts.[28] Because this variable is already rounded by IBES to the nearest cent, we cannot calculate the first post-decimal digit in pro forma EPS *before* rounding. Note, however, that it is difficult simultaneously to round up GAAP and pro forma EPS when they substantially differ from each other. Thus, if firms target pro forma EPS, the extent of quadrophobia in GAAP EPS should be stronger for the subset of firm-quarters where pro forma estimates are sufficiently close to GAAP EPS than for the subset of firm-quarters where the two EPS measures are different.

Accordingly, we divide all firm-quarter observations with analyst coverage into two parts. The first consists of observations for which pro forma EPS as reported by IBES coincides with EPS from Compustat (i.e., GAAP EPS) when rounded to the nearest cent (34% of the sample), and the second consists of observations for which the two figures differ. We then compare the frequency of the number 4 in unrounded GAAP EPS across these two subsamples. Table 6 reports that in almost every year, the frequency of 4 in the first ("Pro forma = GAAP") subsample is significantly smaller than that in the second subsample. Over the entire sample period, the average frequencies of 4 in the two subsamples are 0.0665 and 0.0904, respectively.

We conclude that firms engaging in quadrophobia target earnings measures that are most relevant to analysts and investors (pro forma EPS) and do not target earnings measures that are less relevant for these stakeholders (GAAP EPS when they differ from pro forma). This finding provides further evidence for the third and fourth characteristics in the framework of Burgstahler and Chuk (2017). Moreover, it implies that our main results, which are based on GAAP rather than pro forma

[28]According to the IBES Glossary (2002),"with very few exceptions analysts make their earnings forecasts on a continuing operations basis. This means that IBES receives an analyst's forecast after discontinued operations, extra-ordinary charges, and other non-operating items have been backed out.… IBES adjusts reported earnings to match analyst forecasts on both an annual and quarterly basis. This is why IBES actuals may not agree with other published actuals; i.e., Compustat." We start in 1984 because IBES data are limited prior to 1984.

TABLE 6

Quadrophobia in GAAP Versus Pro Forma EPS

The first row of Table 6 presents the frequency of the number 4 in the first post-decimal digit of GAAP earnings per share (EPS) in the subsample for which pro forma EPS (i.e., actual EPS reported by IBES) coincides with GAAP EPS (i.e., EPS from Compustat, measured as primary EPS before 1997 and as diluted EPS starting in 1997) when rounded to the nearest cent. The second row presents the frequency of the number 4 in the subsample where these 2 EPS numbers are different when rounded to the nearest cent. *Z*-statistics for the test of the hypothesis that the frequency of the number 4 differs across the two subsamples are reported in parentheses. The last 2 columns present the frequency of the number 4 and the number of observations in each subsample combined across all years (1984–2021). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993
Pro forma = GAAP	0.0815	0.0659	0.0678	0.0568	0.0612	0.0621	0.0703	0.0533	0.0504	0.0561
Pro forma ≠ GAAP	0.0897	0.0902	0.0817	0.0859	0.0886	0.0839	0.0767	0.0791	0.0908	0.0713
Z-test	(0.55)	(2.56)**	(1.62)	(3.71)***	(3.71)***	(3.09)***	(0.95)	(3.98)***	(6.33)***	(2.82)**

	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003
Pro forma = GAAP	0.0551	0.0577	0.0540	0.0582	0.0456	0.0507	0.0546	0.0488	0.0552	0.0576
Pro forma ≠ GAAP	0.0823	0.0790	0.0738	0.0956	0.0816	0.0826	0.0812	0.0854	0.0849	0.0871
Z-test	(5.40)***	(4.31)***	(4.37)***	(3.34)***	(6.88)***	(6.76)***	(5.14)***	(6.22)***	(5.11)***	(5.30)***

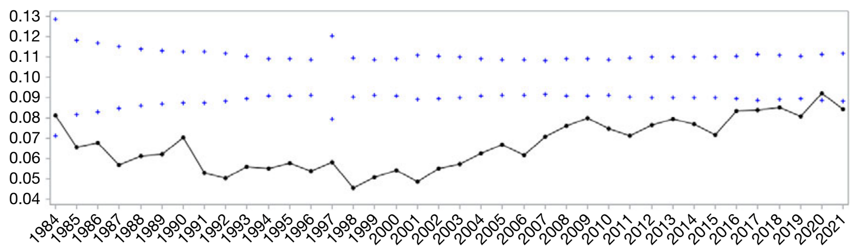
	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Pro forma = GAAP	0.0625	0.0671	0.0619	0.0708	0.0763	0.0802	0.0747	0.0712	0.0764	0.0798
Pro forma ≠ GAAP	0.0897	0.1003	0.0927	0.0952	0.1055	0.0992	0.0974	0.0981	0.0995	0.0975
Z-test	(5.16)***	(6.19)***	(6.06)***	(4.70)***	(4.97)***	(3.22)***	(4.09)***	(4.66)***	(3.86)***	(2.97)***

	2014	2015	2016	2017	2018	2019	2020	2021	All Years	No. of Obs.
Pro forma = GAAP	0.0771	0.0719	0.0833	0.0840	0.0852	0.0810	0.0921	0.0844	0.0665	120,548
Pro forma ≠ GAAP	0.1001	0.1011	0.1041	0.1003	0.0951	0.1021	0.0951	0.1016	0.0904	233,602
Z-test	(3.85)***	(4.82)***	(3.25)***	(2.45)***	(1.54)	(3.25)***	(0.42)	(2.31)**	(24.54)***	

FIGURE 4

Frequency of the Number 4 When Pro Forma and GAAP EPS Coincide

The solid line in Figure 4 presents the frequency of the number 4 in the first post-decimal digit of quarterly EPS in the sample where actual EPS as reported by IBES (i.e., pro forma EPS) coincide with EPS calculated from Compustat (i.e., GAAP EPS) when rounded to the nearest cent. GAAP EPS is calculated as primary EPS before 1997 and as diluted EPS starting in 1997. The blue "plus" marks correspond to 95% confidence intervals around 0.1.



EPS, are likely conservative and understate the prevalence of quadrophobia among publicly reporting companies.

Finally, Table 6 implies that the seeming recent decline in quadrophobia apparent in Graph D of Figure 1 is at least partly driven by firms shifting their rounding efforts toward pro forma EPS. Indeed, although there was a significant underrepresentation of the number 4 in the "Pro forma ≠ GAAP" subsample at the beginning and in the middle of our sample period, it has disappeared in recent years: From 2007 onward, the frequency of 4 in this subsample has been greater than 0.095 in each year. In contrast, quadrophobia is still apparent in the "Pro forma = GAAP" subsample. Figure 4, which is the analog of Graph D of Figure 1 but for the "Pro forma = GAAP" subsample (i.e., it plots the numbers in the first row of Table 6), shows that although the incidence of rounding has declined over time, it is still strongly pronounced even in recent years. This shift toward targeting pro forma, rather than GAAP-based earnings, is consistent with the evidence in Bradshaw and Sloan (2002), who examine earnings announcements disclosures and show an increasing emphasis of managers on pro forma measures over GAAP measures.

2. Initiation and Cessation of Analyst Coverage

To further explore the role of analyst coverage, we note that most firms in our sample were not followed by analysts over the entire trading period. Some firms first received analyst coverage after several years of trading, whereas others lost coverage over time. If the desire to meet analyst forecasts encourages managers to round up earnings, then the incidence of quadrophobia should increase after the introduction of analyst coverage and decrease after the cessation of coverage.

We thus focus on the subsample of firms (56% of the overall sample of 28,459 firms) that were covered by analysts at some point over our sample period; we call them "ever covered by analysts." Approximately 93% of these firms have a reporting history that precedes the initiation of analyst coverage, and the average pre-coverage history is 3 years long. In addition, approximately 32% of firms that have coverage end up losing it, and the average post-coverage history is 5-year long. We define two indicator variables for firms in this subsample: BEFORE_COV (AFTER_COV) equals 1 if the firm-quarter belongs to the period before analyst coverage is initiated for the firm (after all analysts drop coverage). A firm-quarter with both variables equal to 0 corresponds to the period when the firm is followed by at least one analyst.

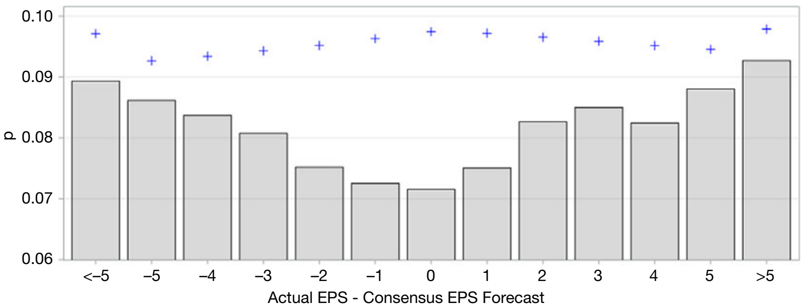
Columns 6 and 7 of Table 5 present the analogs of the models in columns 1 and 2, but focusing on the subsample of "ever covered by analysts" firms and replacing the explanatory variable ANALYST by two variables, BEFORE_COV and AFTER_COV. Both variables are statistically and economically significant. For example, their marginal effects in column 6 are 0.01 and 0.012, implying that the frequency of the number 4 decreases by 0.01 after the initiation of analyst coverage and increases by 0.012 after coverage is dropped. Of course, the initiation and cessation of analyst coverage are both endogenous, so this test does not establish causality, but it is consistent with the idea that analyst coverage motivates firms to engage in quadrophobia.

These results differ from those in Yu (2008), Irani and Oesch (2013), (2016), and Chen et al. (2015), who show that greater analyst coverage decreases the likelihood of accrual-based earnings management, suggesting that analysts play an important monitoring role. A possible reason for these different conclusions is similar to that discussed in Section V.B in the context of executive compensation: Since quadrophobia only requires inflating EPS by a 10th of a cent, it has relatively low costs compared with some other forms of earnings management. As a result, the extra benefits of engaging in quadrophobia to meet analyst expectations are likely high enough to dominate the extra costs of greater scrutiny from analysts.

FIGURE 5

Frequency of the Number 4 as a Function of Earnings Surprise

Figure 5 plots the frequency of the number 4 in the first post-decimal digit of EPS as a function of how close reported EPS are to analyst expectations. The sample consists of all firm-quarter observations with EPS greater than 0.1 cents for which the consensus analyst forecast is available in IBES over the period of 1980 to 2001. The *x*-axis corresponds to the earnings surprise, defined as the difference in cents between actual EPS reported by IBES and the corresponding median analyst forecast. The *y*-axis presents the average frequency of the number 4 in firm-quarter observations with a given earnings surprise. The blue "plus" marks correspond to the lower bound of the 95% confidence interval around 0.1.



3. Rounding to Meet Analyst Expectations and Stock Price Performance

If quadrophobia allows firms to meet analyst forecasts, it should be especially pronounced when the firm's EPS is close to analyst expectations. We thus plot the frequency of the number 4 as a function of the earnings surprise, which we define as the difference between the actual reported EPS from IBES and the most recent consensus (median) analyst forecast prior to the announcement. Figure 5 shows that the number 4 is, indeed, most underrepresented when the firm is close to meeting or narrowly beating expectations: Its frequency is as low as 0.07 when the consensus forecast equals reported EPS. As the magnitude of the earnings surprise increases, the prevalence of strategic rounding declines.

Note, however, that engaging in quadrophobia to meet analyst expectations would be significantly less beneficial if investors could see through this behavior and reacted more negatively if analyst expectations were met through strategic rounding. Whether the market sees through and penalizes rounding behavior is a priori unclear. On the one hand, investors can easily calculate the first post-decimal digit of unrounded EPS. On the other hand, the number 4 can be absent by pure chance (with probability 90% in a random sample), so a given first post-decimal digit is not very informative about whether the firm has rounded up its EPS.

We explore whether the market sees through strategic rounding in Table 7. Panel A reports the average price reaction to earnings announcements, grouped by earnings surprise and by the first post-decimal digit of EPS. We measure the price reaction, CAR(-1,$+1$), using the 3-day cumulative Fama–French 3-factor-adjusted abnormal returns. Consistent with prior literature (e.g., Bhojraj et al. (2009)), the average price reaction is positive if the firm beats analyst forecasts, is negative otherwise, and is monotonically increasing in the earnings surprise. These properties hold for each post-decimal EPS digit.

We next compare the average price reaction to the earnings announcement between two subsamples: i) subsample where the first post-decimal EPS digit is "4," that is, where strategic rounding did not occur, and ii) subsample where the first

TABLE 7

Stock Price Performance Around and After Earnings Announcements

Panel A of Table 7 reports the average CAR(−1,+1) around the earnings announcement grouped by earnings surprise and the first post-decimal earnings per share (EPS) digit for observations with EPS exceeding 0.1 cents. Earnings surprise (in cents) is IBES-reported actual EPS minus the most recent median analyst forecast prior to the earnings announcement. CAR(−1,+1) is the 3-day Fama–French 3-factor-adjusted cumulative abnormal return, where day 0 is the day of the earnings announcement. The number of observations for each group is reported to the right of the average CAR. The panel also presents, for each earnings surprise group, the difference between the average CAR when the first post-decimal EPS digit is "4" and when it is "5" (Diff: "4" − "5"), as well as the *p*-value for the test that this difference is 0. The last 4 rows combine numbers "0–4" in one group (EPS is rounded down) and "5–9" in the other (EPS is rounded up) and present the difference in CARs between these two groups (Diff: "0–4" − "5–9") and the corresponding *p*-value. Panels B and C analyze the subsample from Panel A where firms just meet or narrowly beat analyst expectations, that is, the earnings surprise is either 0 or 1 cent. Panel B reports the average CAR(−1,+1) grouped by the first post-decimal EPS digit and the Q-score, $Q^{(N)}$, as defined in Section III, as well as the same tests for differences between subsamples (based on rounding-up vs. rounding-down of EPS) as in Panel A. In addition, for each *N*, the column "*p*-Value" reports the *p*-value for the test that when the first post-decimal EPS digit is "5" (or "5–9"), the difference in CARs between the subsamples with $Q^{(N)} = 0$ and $Q^{(N)} = 1$ is 0. Panel C presents both short-term (CAR(−1,+1)) and long-term (CAR (+1,+*T*) for *T* = 30, 90, 180, and 365 days) stock price performance grouped by the first post-decimal EPS digit, and the same tests for differences between subsamples (based on rounding-up vs. rounding-down of EPS) as in Panel A. CAR(+1,+*T*) is the Fama–French 3-factor-adjusted cumulative abnormal return over *T* days, where day 0 is the day of the earnings announcement.

Panel A. CAR(−1,+1)

	Earnings Surprise									
Digit	≤ −2	No. of Obs.	−1	No. of Obs.	0	No. of Obs.	1	No. of Obs.	≥2	No. of Obs.
0	−2.21%	7,535	−1.01%	2,515	−0.22%	5,415	0.69%	4,362	2.48%	13,914
1	−2.33%	6,969	−1.05%	2,171	−0.35%	4,636	0.68%	3,810	2.47%	13,347
2	−2.03%	6,675	−0.65%	2,055	−0.09%	4,058	0.81%	3,511	2.43%	12,765
3	−2.17%	6,345	−1.03%	1,850	−0.26%	3,849	0.59%	3,356	2.40%	12,606
4	−2.09%	6,032	−1.11%	1,649	−0.35%	3,453	0.92%	2,980	2.32%	11,816
5	−2.25%	7,852	−1.45%	2,560	−0.29%	5,314	0.48%	4,430	2.41%	13,828
6	−2.16%	7,712	−1.16%	2,637	−0.27%	5,505	0.82%	4,552	2.61%	14,094
7	−2.25%	7,560	−1.12%	2,618	−0.41%	5,470	0.61%	4,665	2.56%	14,070
8	−2.21%	7,473	−1.16%	2,374	−0.21%	5,261	0.86%	4,317	2.50%	13,834
9	−2.07%	7,396	−1.03%	2,491	−0.18%	5,480	0.80%	4,498	2.45%	14,031
Diff: "4" − "5"	0.16%		0.34%		−0.06%		0.44%		−0.09%	
p-Value	0.23		0.12		0.67		0.01		0.42	
0–4	−2.17%	33,556	−0.97%	10,240	−0.25%	21,411	0.73%	18,019	2.42%	64,448
5–9	−2.19%	37,993	−1.18%	12,680	−0.27%	27,030	0.71%	22,462	2.51%	69,857
Diff: "0–4" − "5–9"	0.02%		0.22%		0.02%		0.02%		−0.08%	
p-Value	0.73		0.01		0.75		0.79		0.06	

Panel B. CAR(−1,+1) When Firms Meet or Narrowly Beat Analyst Forecasts

	$Q^{(4)}$			$Q^{(10)}$			$Q^{(20)}$		
Digit	$Q^{(4)}=0$	$Q^{(4)}=1$	*p*-Value	$Q^{(10)}=0$	$Q^{(10)}=1$	*p*-Value	$Q^{(20)}=0$	$Q^{(20)}=1$	*p*-Value
0	0.21%	0.18%		0.15%	0.35%		0.21%	0.26%	
1	0.21%	0.12%		0.11%	0.13%		0.07%	0.24%	
2	0.39%	0.34%		0.29%	0.40%		0.31%	0.24%	
3	0.10%	0.15%		−0.03%	0.38%		0.17%	0.14%	
4	0.33%	0.18%		0.23%	0.25%		0.18%	0.14%	
5	−0.02%	0.09%	0.52	0.13%	0.06%	0.66	0.05%	0.06%	0.96
6	0.22%	0.23%		0.18%	0.29%		0.22%	0.23%	
7	0.24%	0.03%		0.12%	0.15%		0.03%	0.24%	
8	0.11%	0.31%		0.06%	0.36%		0.22%	0.13%	
9	0.24%	0.27%		0.16%	0.32%		0.13%	0.49%	
Diff: "4" − "5"	0.35%	0.09%		0.11%	0.19%		0.13%	0.09%	
p-Value	0.10	0.49		0.49	0.28		0.33	0.49	
0–4	0.25%	0.19%		0.15%	0.30%		0.19%	0.21%	
5–9	0.16%	0.18%	0.73	0.13%	0.24%	0.10	0.13%	0.23%	0.19
Diff: "0–4" − "5–9"	0.09%	0.01%		0.02%	0.07%		0.06%	−0.02%	
p-Value	0.33	0.89		0.78	0.33		0.31	0.87	

Panel C. Short-Term and Long-Term CARs When Firms Meet or Narrowly Beat Analyst Forecasts

	CAR					
Digit	(−1,+1)	(+1,+30)	(+1,+90)	(+1,+180)	(+1,+365)	No. of Obs.
4	0.24%	−0.27%	−1.08%	−2.74%	−6.47%	6,433
5	0.06%	−1.04%	−2.70%	−5.73%	−11.53%	9,744
Diff: "4" − "5"	0.18%	0.77%	1.62%	2.99%	5.06%	
p-Value	0.11	0.00	0.00	0.00	0.00	
0–4	0.20%	−0.73%	−1.89%	−4.15%	−8.59%	39,430
5–9	0.18%	−0.85%	−2.43%	−4.98%	−9.82%	49,492
Diff: "0–4" − "5–9"	0.02%	0.11%	0.55%	0.83%	1.23%	
p-Value	0.63	0.25	0.00	0.01	0.03	

post-decimal digit is "5," that is, where it is more likely that management strategically rounded up EPS. If investors see through quadrophobia, the price reaction to meeting or narrowly beating analyst forecasts should be lower in the second subsample, compared with the first. As Panel A of Table 7 reports, there is no robust evidence that this is the case. Although the price reaction is lower (more negative or less positive) in the subsample with a "5" when the firm misses analyst expectations or when the earnings surprise is exactly 1 cent, this pattern is reversed when the firm just meets expectations and when the earnings surprise exceeds 1 cent. Moreover, the difference between the two subsamples is not statistically significant in most earnings surprise categories. Although the difference is statistically significant when the earnings surprise is exactly 1 cent, it is not robust to considering other numbers. For example, the price reaction when the first post-decimal digit is "6" or "7" (0.82% and 0.61%) is actually higher than when it is "3" (0.59%), and if we aggregate numbers "0–4" in one subsample and "5–9" in the second, the difference in CARs between these subsamples is 0.02% and not statistically significant.

It could be that for a random firm that just happens to have a "5" in its first post-decimal digit, investors do not attribute the presence of the "5" to strategic rounding. However, if investors see through quadrophobia, they should be more suspicious of firms that have consistently rounded up their EPS in the past. Thus, in Panel B of Table 7, we examine whether the price reaction to rounding up depends on the firm's Q-score. We focus on observations where the firm just meets or beats expectations (i.e., the earnings surprise is 0 or 1 cent) and calculate CAR(−1,+1) around the announcement date for two subsamples: Q-score equal to 0 (past quadrophobia is less likely) and Q-score equal to 1 (past quadrophobia is more likely). Panel B reveals that even for persistent quadrophobes (Q-score = 1), the market reaction when their first post-decimal EPS digit is "4" is not statistically different from when it is "5" (or "0–4" vs. "5–9," respectively).

In addition, if investors recognize quadrophobia, then the price reaction when the first post-decimal digit is "5" (or "5–9") should be lower for firms whose Q-score equals 1 than for those whose Q-score equals 0, because "5" (or "5–9") presents stronger evidence of deliberate rounding-up if the firm has engaged in rounding in the past. However, the price reaction to rounding-up is mostly higher, rather than lower, for $Q^{(N)} = 1$ compared with $Q^{(N)} = 0$, and none of the differences is statistically significant (see the 3 columns marked "*p*-Value" in Panel B of Table 7).

Although investors do not see through quadrophobia in the short run, it is possible that they are nevertheless not misled in the long run. To study this question, we analyze whether the return pattern reverses over a longer time horizon. In particular, we consider 1-, 3-, 6-, and 12-month cumulative Fama–French 3-factor-adjusted abnormal returns after the earnings announcement date, that is, CAR(+1,+*T*), for *T* between 30 days and 365 days. Panel C of Table 7 examines whether the long-term stock price performance for firms that just meet or beat analyst forecasts by rounding up, that is, that have "5" (or "5–9") in their first post-decimal digit, is worse than for firms that round down, that is, whose first post-decimal digit is "4" ("0–4," respectively). Although the two groups of firms perform equally well in the 3-day window around the announcement, firms

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that round up start consistently underperforming firms that round down over the 3-month horizon, and this underperformance becomes even more apparent over 6 and 12 months. Both our short-term and long-term return patterns are consistent with the findings in Bhojraj et al. (2009), who study investors' reaction to other forms of earnings management used to beat analyst expectations (the use of income-increasing accruals and cuts in discretionary spending).

Taken together, there is a short-term benefit for firms to engage in quadrophobia so as to meet or beat analyst expectations, but investors do not seem to be misled in the long run. However, the return reversal may be happening not because investors eventually recognize strategic rounding, but rather because rounding-up firms experience a deterioration of their overall performance.

D. Incentives Related to Covenant Violations

Finally, we explore another benefit of earnings management, coming from firms' interactions with creditors and, in particular, debt covenants. The literature has proposed two hypotheses. The first is that firms manipulate financial metrics to avoid violating covenants. The evidence for this hypothesis is mixed: For example, Dichev and Skinner (2002), Sweeney (1994), and Franz, HassabElnaby, and Lobo (2014) find supporting results, whereas DeAngelo et al. (1994) and Healy and Palepu (2001) do not. The second hypothesis, first proposed by DeFond and Jiambalvo (1993), (1994) and explored in the subsequent literature, is that even if manipulation is not used to avoid covenant violations per se, inflating earnings in anticipation of a violation can "enhance the apparent financial strength of the company" and thereby "help the manager's bargaining position in renegotiation of the debt" upon the violation. Consistent with this hypothesis, DeFond and Jiambalvo (1994) find that abnormal accruals are significantly positive in the year *preceding* the year of a covenant violation.

We study strategic rounding in the context of both these hypotheses, which we call the "covenant-violation avoidance" and "bargaining power" hypotheses. With respect to the first hypothesis, strategic rounding differs from other earnings management tools explored in this literature because covenant thresholds are typically not directly linked to *per-share* earnings, and thus inflating EPS by an additional cent is unlikely to help firms avoid violating covenants.[29] Although covenants are not linked to EPS, they are often linked to EBIT or EBITDA (e.g., interest coverage ratio or leverage ratio covenants) and working capital (e.g., current ratio covenants), which can be manipulated via earnings-increasing or working capital accounts procedures (DeFond and Jiambalvo (1993)). Accordingly, papers that find support for the covenant-violation avoidance hypothesis measure manipulation via discretionary accruals and real earnings management (Franz et al. (2014)) or changes in accounting methods Sweeney (1994)).[30]

[29]The Supplementary Material of Roberts and Sufi (2009) describes the distribution of different types of covenants.

[30]Dichev and Skinner's (2002) key piece of evidence is that firms cluster just above covenant thresholds, but they cannot identify the forms of earnings management that firms use to avoid covenant violations.

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Even though firms are less likely to round up EPS to avoid covenant violations, strategic rounding can still be used to project financial strength and strengthen firms' bargaining position. Hence, a priori, we expect to find relatively weaker support for the covenant-violation avoidance hypothesis, but potentially stronger support for the bargaining power hypothesis.

Our sample for this analysis consists of firm-quarter observations with available data on the presence or absence of covenant violations for the current fiscal quarter. We use the covenant violations database that was originally constructed for the analysis in Roberts and Sufi (2009). It contains all covenant violations reported in SEC filings between 1996 and 2012 for publicly traded U.S. firms and identifies the quarter of the violation.[31]

To test the first hypothesis, we note that if firms use quadrophobia to avoid violating covenants, then the likelihood of a covenant violation should be positively related to the *contemporaneous* frequency of the number 4 in the first post-decimal digit of EPS.[32] However, we do not find any evidence of such a contemporaneous relationship (Table A6 in the Supplementary Material).

On the other hand, if firms approaching a covenant violation use strategic rounding prior to the violation to improve their future bargaining power with creditors, then the likelihood of a covenant violation should be negatively related to the frequency of the number 4 in the *preceding* quarters. In particular, we follow DeFond and Jiambalvo (1994), who study abnormal accruals in the year preceding the year of a violation, and examine the frequency of the number 4 in the year (i.e., four quarters) preceding the year of the violation. Our key explanatory variable for a firm-quarter (i,t) is thus $Q_{i,t}^{(4)}$, as defined by equation (1), which equals 0 if firm i had at least one "4" in its post-decimal EPS digit over four quarters with positive earnings prior to but not including quarter t, and set to 1 otherwise. Table 8 reports that the likelihood that the firm violates a covenant over the next year (i.e., in one of the quarters $\{t,\ldots,t+3\}$) is significantly positively related to $Q^{(4)}$. This relationship is robust to controlling for discretionary accruals and other firm characteristics, including measures of the firm's financial health (leverage and current ratio), as well as year fixed effects.[33]

[31]The data are available on Michael Roberts' academic website. As noted in Roberts and Sufi (2009), the SEC does not require firms to detail which covenant was violated, so the information about the type of covenant is not available from the database.

[32]To see this, note that all firm-quarter observations can be split into two sets, A and B: Firm-quarters in set A are those right at the EPS covenant threshold, such that a covenant violation occurs if the first post-decimal digit is 4 and EPS is rounded down, but does not occur if this digit is a 5 and EPS is rounded up. Firm-quarters in set B are those for which inflating EPS by 1 cent does not affect whether the firm violates a covenant or not (either because the firm is strictly below or above an EPS-based threshold or because no covenant threshold is tied to EPS). If firms use quadrophobia to avoid covenant violations, then: i) firms in set A should avoid the number 4 and, as a result, avoid violating the covenant, whereas ii) the frequency of the number 4 in set B should be unrelated to the incidence of covenant violations. Hence, in the combined sample (A and B), the frequency of the number 4 should be positively related to the incidence of covenant violations.

[33]To be consistent with DeFond and Jiambalvo (1994), we use the signed residuals from the modified Jones model, that is, before taking their absolute values. The significant positive coefficient on these residuals in Table 8 confirms the result of DeFond and Jiambalvo (1994) that abnormal accruals are significantly positive in the year preceding the year of covenant violation. However, the coefficient for

TABLE 8

Strategic Rounding Prior to Covenant Violations

Table 8 presents probit regressions, where the dependent variable for firm-quarter (i,t) is set to 1 if firm i has a covenant violation over the next year, that is, in at least one of the quarters $\{t,\ldots,t+3\}$, and to 0 otherwise. The sample consists of firm-quarter observations with available data on the presence or absence of covenant violations over the period of 1996 to 2012. The main explanatory variable is the Q_SCORE, $Q_{i,t}^{(4)}$, as defined by equation (1), which equals 0 if firm i had at least one "4" in the first post-decimal earnings per share digit over four quarters with positive earnings prior to but not including quarter t, and set to 1 otherwise. AB_ACC is the (signed) residuals from the modified Jones model, which is estimated cross-sectionally for every 2-digit SIC code and year (i.e., it is computed as JONES_RES, but before taking the absolute value of the residuals). SIZE is the logarithm of total assets. M/B is the market value of total assets divided by the book value of total assets. ISSUE is an indicator variable that is set to 1 if the firm issued securities during the year. LEVERAGE is the sum of short-term and long-term debt scaled by total assets. CURRENT_RATIO is the absolute value of the ratio between current assets and current liabilities. Each continuous variable is winsorized at 1% and 99%. t-Statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Covenant Violation over the Next Year				
	1	2	3	4	5
Q_SCORE	0.04***	0.03**	0.05***	0.05***	0.04***
	(4.49)	(3.66)	(5.45)	(4.79)	(4.18)
AB_ACC		0.04***	0.05***	0.06***	0.05***
		(4.85)	(4.84)	(6.22)	(4.91)
SIZE			−0.14***	−0.15***	−0.15***
			(−67.00)	(−69.92)	(−68.52)
M/B			−0.11***	−0.13***	−0.13***
			(−30.69)	(−33.94)	(−33.19)
ISSUE			−0.46***	−0.43***	0.05
			(−14.86)	(−13.82)	(0.85)
LEVERAGE				0.34***	0.32***
				(25.83)	(23.99)
CURRENT_RATIO				−0.06***	−0.06***
				(−25.33)	(−25.24)
Constant	−1.83***	−1.74***	−0.86***	−0.71***	−1.21***
	(−257.84)	(−225.09)	(−60.70)	(−43.71)	(−41.93)
No. of obs.	401,575	301,553	287,996	277,749	277,749
Year FE	No	No	No	No	Yes

Combined, these results provide suggestive evidence that firms engage in quadrophobia to strengthen their bargaining power in anticipation of covenant violations, but that unlike other forms of earnings management, quadrophobia is not used to avoid covenant violations per se. Our conclusions are in line with the survey-based evidence in Graham, Harvey, and Rajgopal (2005), who ask CFOs about the factors motivating them to meet earnings benchmarks, such as analyst forecasts of EPS and previously reported EPS. Although they find low unconditional support for the avoidance of covenant violations as a motivation to meet EPS benchmarks (consistent with our results in Table A6 in the Supplementary Material), they also conclude that firms that are closer to technical default consider covenants to be a relatively more important motivation to meet EPS benchmarks (consistent with the bargaining power story; see Section 3.3.5 of their paper).

E. Summary

Taken together, Sections V.A–V.D show that quadrophobia satisfies the four characteristics outlined by Burgstahler and Chuk (2017) and, in particular, is more

the Q-score and its standard error remain unchanged if we use the absolute value of the modified Jones residuals, like in all our other tests.

pronounced when the benefits of inflating EPS by an additional cent are higher and the costs are lower. Moreover, as our comparisons to the literature highlight, the costs and benefits of this form of earnings management are somewhat different from those of other earnings management tools. We discuss the implications of these findings in Sections VI and VIII.

VI. Discussion

In this section, we evaluate the evidence presented so far and discuss the advantages and disadvantages of using quadrophobia to measure earnings management.

An advantage of our measure is its simplicity and transparency; it can be quickly constructed for a broad set of firms using minimal data (total earnings and number of shares outstanding). Another advantage is that the underrepresentation of the number 4 directly measures aggressive accounting practices. In contrast, tests based on accrual-based measures are joint tests of the underlying theory and the researcher's model of discretionary accruals, and these measures are often criticized for being systematically correlated with firm fundamentals, which can lead to the correlated omitted variable problem (see McNichols (2000), Kothari et al. (2005), Dechow et al. (2010), and Owens et al. (2017), for detailed discussions). Therefore, our measure can be particularly useful when studying managerial incentives for earnings management (such as the analysis in Section V) or its consequences.

Note also that since quadrophobia typically involves little accounting discretion and thus has relatively low costs, it can be more sensitive to the benefits of inflating earnings than other, more serious and more costly forms of earnings management. As discussed in Sections V.B and V.D, this can explain why our analysis of executive compensation and analyst coverage yields different results compared with those in the prior literature. Thus, using our measure could make it easier to identify the factors that encourage managers to misreport, but these results would not necessarily extend to other forms of earnings management.

Another difference is that unlike several other measures in the literature, quadrophobia captures the combined use of multiple mechanisms used to manage earnings. As Burghstahler and Chuk (2017) emphasize, "there is an essentially unlimited list of real operating, financing, and investing decisions … and accrual decisions … that can be used to manage earnings." The literature has extensively examined such individual mechanisms, including the management of different types of accruals, changing the classification of items in the income statement, and several forms of real earnings management (see Dechow et al. (2010) for a review). Many of these mechanisms can be potentially used to round up reported EPS.

The benefit of measuring the combined use of multiple mechanisms is that one can identify some firms with aggressive accounting practices that cannot be identified using measures based on specific mechanisms (since different firms may use different mechanisms). Consistent with this idea, Section IV shows that the Q-score helps predict accounting violations even beyond what measures constructed using individual mechanisms, such as those based on the management of accruals, can predict.

The disadvantage of our measure relative to those based on specific mechanisms is that it cannot identify the exact timing of earnings management. A high Q-score indicates that the firm had a low frequency of the number 4 in its first post-decimal EPS digit over the past quarters, but does not indicate in which specific quarters (if at all) a "4" was deliberately changed to a "5." In this sense, the Q-score can help quickly identify the set of likely violators, as it probably did for the SEC's investigations discussed in Section IV.D, but a more careful analysis of these firms' financial statements is necessary to determine whether and when earnings management occurred, and which mechanisms of inflating earnings were used.

In Section A.1 of the Supplementary Material, we provide a discussion and analysis of the specific mechanisms used by firms to round up their EPS. Given the limited time available to managers between identifying the first post-decimal digit in their unrounded EPS and the earnings announcement, certain mechanisms (e.g., working capital accruals management) are more easily implementable than others (e.g., real earnings management). Consistent with this idea, we find no evidence that firms engage in real earnings management, such as cutting R&D or maintenance expenses, to round up their EPS. Instead, we conclude that the manipulation of working capital accruals and changing the classification of items in the income statement are the more likely mechanisms used to achieve rounding-up.

VII. Robustness

In this section, we discuss the robustness of our main results to alternative specifications and other definitions of the Q-score.

A. Firm-Quarter-Level Predictive Regressions

We perform our baseline predictive regressions at the firm-year level (Tables 3 and 4, and Table A7 in the Supplementary Material), in order to match the literature and be able to control for the variables used in prominent prediction models. Table A8 in the Supplementary Material reports that the predictive power of the Q-score is also strong in firm-quarter level regressions. We repeat the specification in column 1 of Table 3, but using firm-quarter level observations for both the Q-scores and the incidence of AAERs and restatements. The coefficients on the Q-scores are similar to those in the firm-year level analysis and are strongly significant; they also remain significant after controlling for discretionary accruals and several additional firm characteristics.

B. Performance-Matched Discretionary Accruals

In our predictive tests up to this point, we measure discretionary accruals using the modified Jones model. Kothari et al. (2005) suggest controlling for the normal level of accruals conditional on ROA, so as to address the concern that firm performance is correlated with the residuals from the modified Jones model. We follow Kothari et al. (2005) and identify a firm from the same industry with the closest level of ROA to that of the focal firm, and then deduct the matched firm's discretionary accruals from those of the focal firm to estimate "performance-matched" residuals. Table A9 in the Supplementary Material repeats Table A8, but with discretionary accruals based on the modified Jones model replaced by performance-matched discretionary accruals. The predictive power of the Q-scores remains similar to that in our main tests.

C. "Four" Versus Other Numbers

Our analysis focuses on the number 4 since the amount of discretion needed to increase the reported EPS by 1 cent is minimized when the first post-decimal digit is a 4, and since this allows us to derive the simplest possible measure. However, Table 1 also reports a strong underrepresentation of numbers 2 and 3, and a consistent underrepresentation of these numbers together with the number 4 could also be a signal of aggressive financial reporting practices. In unreported results, we show that the underrepresentation of numbers 2 and 3 is persistent, although less so than for the number 4. We thus study an alternative to the Q-score: A composite score of strategic rounding that combines the number 4 with the number 3 (or both 2 and 3). Specifically, SCORE$^{(N)}$[3,4] (and by analogy, SCORE$^{(N)}$[2,3,4]) in quarter t is set to 0 if there was at least one "3" or "4" (at least one "2," "3," or "4") in the first post-decimal digit of EPS reported by the firm over N quarters with positive earnings prior to but not including quarter t, and set to 1 otherwise. Table A10 in the Supplementary Material analyzes the predictive power of SCORE$^{(N)}$[3,4] and SCORE$^{(N)}$[2,3,4] for $N = 4$ and 10, and reports that all of these composite scores are positive and significant in predicting both AAERs and restatements.

D. Predicting Class Action Litigation

In Table A11 in the Supplementary Material, we examine whether the Q-scores can also predict class action securities fraud litigation. The class action litigation data are from the Stanford Law School/Cornerstone Research Securities Class Action Clearinghouse and cover 1,222 lawsuits filed between 1996 and 2012. The class action data set defines the period over which the alleged fraud was uncorrected in the market, and we refer to this period as the "alleged violation period." To match our specifications for AAERs and restatements, we set the dependent variable for firm-quarter pair (i,t) to 0 if the firm never experiences a class action lawsuit after quarter t or if the alleged violation period starts later than 5 years after quarter t, and to 1 otherwise. The coefficient estimate on the Q-score is positive and significant, with a similar magnitude as for restatements and AAERs, and is robust to controlling for discretionary accruals and additional firm characteristics.

E. Q-Score Using only the First Three Fiscal Quarters

Our construction of the Q-score is based on N prior quarters with positive earnings, some of which could be fourth quarters. This may raise potential concerns given the uniqueness of fourth quarters: Prior literature has documented a lower likelihood of earnings management in the fourth quarter relative to the first three quarters and even some reversal of earnings management, potentially because auditors are involved in the fourth quarter and annual audit process. We thus reconstruct the Q-score based solely on preceding observations from the first three fiscal quarters. As we report in Table A12 in the Supplementary Material, strategic rounding using the modified Q-score is still strongly persistent, so the modified Q-score can also be used to measure an aggressive approach to financial reporting.

VIII. Policy Implications and Conclusion

This article develops a simple and transparent measure of accounting aggressiveness based on the distribution of digits in EPS data. Specifically, if firms manage earnings to increase their reported EPS by 1 cent, then the number 4 should be underrepresented in the first post-decimal digit of EPS data, a pattern we call "quadrophobia." We show that quadrophobia is pervasive, persistent, and is particularly pronounced when inflating earnings allows managers to increase their compensation, meet analyst expectations, or strengthen their bargaining position upon covenant violations. Accordingly, our measure of accounting aggressiveness, the Q-score, captures the history of quadrophobia in a given firm by quantifying the frequency of the number 4 in the first post-decimal digit of its past EPS. We show that firms with a history of quadrophobia are more likely to engage in potentially problematic accounting practices that lead to restatements, SEC enforcement actions, and class action securities fraud litigation. Moreover, the Q-score predicts accounting violations even after controlling for other measures used in the literature and helps improve the predictive power of existing models.

Note that the dollar amounts involved in quadrophobia can be relatively small. For example, in 2021, the mean (median) aggregate amount of earnings over which management would have to exercise discretion in order to move quarterly EPS by a 10th of a cent is \$335,000 (\$58,000), or 0.13% (0.22%) of the firm's quarterly earnings.[34] If the focus is on the quantitative materiality of the dollars at issue, one could argue that quadrophobia is not a major problem in the market.

SAB 99, however, suggests that both qualitative and quantitative factors should be considered in determining materiality: Even small dollar amounts can be material if they are likely to affect stock prices, hide "a failure to meet analysts' consensus expectations," or have "the effect of increasing management's compensation," among other considerations.[35] Our findings relating quadrophobia to analyst forecasts, executive compensation, and covenant violations are thus consistent with the broader concern expressed in SAB 99. Moreover, the fact that quadrophobia predicts future restatements, SEC enforcement actions, and class action litigation suggests that even if strategic rounding reflects the exercise of legitimate accounting judgment, its presence signals an aggressive accounting culture that manifests in different ways and increases exposure to enforcement proceedings and litigation.

Quadrophobia can thus be a useful indicator of concern regarding the quality of public company financial statements. Our findings appear to have motivated the SEC's "EPS Initiative" program, resulting in several enforcement actions against

[34]An increase of \$0.001 in EPS requires increasing aggregate earnings by $M \times 0.001$, where M is the number of shares outstanding. The mean (median) quarterly earnings for companies with positive earnings in 2021 are \$255 million (\$26 million), and the mean (median) number of shares outstanding is \$335 million (\$58 million).

[35]See SEC Staff Accounting Bulletin No. 99 at https://www.sec.gov/interps/account/sab99.htm.

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firms that have demonstrated persistent quadrophobia. It will be interesting to study whether investors are more likely to recognize and discount strategic rounding following the EPS Initiative's enforcement actions, and whether the prevalence of quadrophobia will substantially decrease.

Appendix. Variables Used in Predictive Regressions of AAERs and Restatements

Q_SCORE$^{(N)}$: Indicator variable that is set to 0 if there was at least one 4 in the first post-decimal digit of EPS reported by the firm over N quarters with positive earnings prior to but not including the current quarter, and set to 1 otherwise.

JONES_RES: Absolute value of the residuals from the modified Jones model (Dechow et al. (1995)), which is estimated cross-sectionally for every 2-digit SIC code and year. For each year and each 2-digit SIC code, we estimate the regression $\frac{\text{ACCRUALS}_t}{\text{TA}_{t-1}} = \alpha_0 + \alpha_1 \frac{1}{\text{TA}_{t-1}} + \alpha_2 \frac{\Delta\text{SALES}_t - \Delta\text{REC}_t}{\text{TA}_{t-1}} + \alpha_3 \frac{\text{PPE}_t}{\text{TA}_{t-1}} + \varepsilon_t$, where TA_{t-1} are lagged total assets; ΔSALES_t and ΔREC_t are changes in sales and receivables, respectively; PPE_t is net property, plant, and equipment; and ACCRUALS_t are total accruals, defined as the change in current assets minus the change in cash holdings, minus the change in current liabilities excluding the current portion of long-term debt, and minus depreciation and amortization. JONES_RES is the absolute value of the residuals from this regression.

JONES_RES_PM: Computed by first matching a firm-year observation with another from the same 2-digit SIC industry and fiscal year with the closest ROA and then deducting the matched firm's discretionary accruals from those of the sample firm, as in Kothari et al. (2005).

Eight Variables from Beneish's M-Score Model

DAYS_SALES_IN_RECEIVABLES: Ratio of days' sales in receivables in year t to year $t-1$.

GROSS_MARGIN_INDEX: Ratio of gross margin in year $t-1$ to gross margin in year t.

ASSET_QUALITY_INDEX: Ratio of asset quality in year t to asset quality in year $t-1$, where asset quality in a given year is (1 − Current assets + PP&E)/Total assets.

SALES_GROWTH_INDEX: Ratio of sales in year t to sales in year $t-1$.

LEVERAGE_INDEX: Ratio of total debt to total assets in year t relative to the corresponding ratio in year $t-1$.

DEPRECIATION_INDEX: Ratio of the rate of depreciation in year $t-1$ to the rate of depreciation in year t.

TOTAL_ACCRUALS_TO_TOTAL_ASSETS_RATIO: Ratio of total accruals (change in working capital accounts other than cash less depreciation) to total assets.

SG&A_INDEX: Ratio of SG&A expenses to sales in year t relative to the corresponding measure in year $t-1$.

Nine Variables from Dechow et al.'s F-Score Model 2

RSST_ACCRUALS: Richardson, Sloan, Soliman, and Tuna (2006) accruals.

CHANGE_IN_RECEIVABLES: Change in accounts receivables divided by average total assets.

CHANGE_IN_INVENTORY: Change in inventory divided by average total assets.

PERCENT_SOFT_ASSETS: (Total assets − PP&E − Cash and cash equivalent) divided by total assets.

CHANGE_IN_CASH_SALES: Sales minus change in accounts receivable.

CHANGE_IN_ROA: Change in return on assets (ROA), where ROA is the income before extraordinary items scaled by total assets.

ABNORMAL_CHANGE_IN_EMPLOYEES: Percentage change in the number of employees minus percentage change in assets.

OPERATING_LEASES_FLAG: Indicator variable that is set to 1 if future operating lease obligations are greater than 0.

SECURITY_ISSUE_FLAG: Indicator variable that is set to 1 if the firm issued securities during the year (SSTK > 0 or DLTIS > 0).

Additional 11 Predictive Variables from Alawadhi et al.

MARKET_CAPITALIZATION: Product of price and total shares outstanding.

M/B: Market value of total assets divided by the book value of total assets.

LEVERAGE: Sum of short-term and long-term debts scaled by total assets.

PROFIT_MARGIN: Ratio of net income to sales.

ROA: Income before extraordinary items scaled by total assets.

BASIC_EARNINGS_POWER: Ratio of operating income after depreciation to total assets.

ALTMAN_Z_SCORE: Generalized version of the Altman *Z*-score, calculated as
$Z = 3.25 + 6.56 \times X1 + 3.26 \times X2 + 6.72 \times X3 + 1.05 \times X4$, where
$X1$ = (Current assets − Current liabilities)/Total assets
$X2$ = Retained earnings/Total assets
$X3$ = EBIT/Total assets
$X4$ = (Total assets − Total liabilities)/Total liabilities.

DISTRESS_FLAG: Indicator variable that is set to 1 if Altman *Z*-score < 1.75.

INDICATOR_FOR_ACCOUNTING_LOSSES: Indicator variable that is set to 1 if net income is negative.

INTANGIBLES_TO_TOTAL_ASSETS: Ratio of total intangible assets to total assets.

INVENTORY_TURNOVER: Ratio of cost of goods sold to inventory.

Supplementary Material

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