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Do baths muddy the waters or clear the air? ☆

K. Stephen Haggard [a], John S. Howe [b,*], Andrew A. Lynch [c]

[a] Department of Finance and General Business, College of Business, Missouri State University, USA
[b] Department of Finance, Robert J. Trulaske, Sr. College of Business, University of Missouri, USA
[c] School of Management, Binghamton University, USA

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ABSTRACT

We examine the information environments of firms following large, non-recurring charges ("baths"). We test competing hypotheses about the consequences of a bath—a bath either improves the information environment (the transparency hypothesis) or degrades it (the opacity hypothesis). Difference-in-differences analysis suggests that after a bath (1) earnings become smoother, (2) firm-level information asymmetry decreases, and (3) stock returns become more responsive to unexpected earnings. We interpret these findings as supportive of the transparency hypothesis. We also document that the relative improvement in the information environment is greater for baths that are not voluntary, consistent with managerial obfuscation prior to the bath.

1. Introduction

We examine changes in firms' information environments associated with large, non-recurring charges ("baths"). Our primary research question is: Does a bath lead to an enhanced information environment or a degraded one? On one hand, if the bath credibly realigns reported values with economic values (e.g., by writing down tangible and intangible assets, incurring restructuring charges, or acknowledging litigation losses), the bath enhances the firm's information environment (Elliott and Shaw, 1988; Francis et al., 1996). We refer to this scenario as the transparency hypothesis. Alternatively, a bath might hide ongoing poor operating performance (see e.g., Moore, 1973; Healy, 1985; Kothari et al., 2009b). Large charges on the income statement reduce the inferred precision of that period's earnings (Kirschenheiter and Melumad, 2002) and many of these charges can be reversed at a later date to artificially inflate future earnings (Bens and Johnston, 2009). In this scenario, baths obscure operating underperformance. We refer to this scenario as the opacity hypothesis.

Using difference-in-differences analysis, we examine three aspects of the quality of a firm's information environment and find evidence consistent with the transparency hypothesis. Specifically, following a bath, earnings become smoother, firm-level information asymmetry decreases, and stock returns become more responsive to unexpected earnings. In short, baths appear to "clear the air" on average, consistent with the transparency hypothesis.

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* Corresponding author.
E-mail addresses: shaggard@missouristate.edu (K.S. Haggard), howej@missouri.edu (J.S. Howe), lynch@binghamton.edu (A.A. Lynch).

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As described by Kothari et al. (2009b), managers withhold bad news until some threshold is reached, at which time the negative information is released. A bath is an extreme example of this phenomenon. However, managers might differ in their willingness to withhold bad news. To explore this possibility, we classify the baths in our sample as voluntary or forced. Forced baths are associated with bigger improvements in the information environment (i.e., a greater reduction in information asymmetry) relative to voluntary baths, consistent with managerial obfuscation prior to the bath. We document that firms that are forced to take a bath have weaker corporate governance than firms that voluntarily take a bath. Weaker governance might allow a greater accumulation of bad news pre-bath and, consequently, a greater reduction in information asymmetry post-bath.

Our empirical analysis employs propensity score matching to create a sample of 5,546 baths and 5,546 matching non-baths. Our first analysis examines changes in firm earnings following baths. Relative to matched firms, earnings improve significantly post-bath and earnings become smoother. Specifically, we find that bath firms are more likely to have a small profit and a small increase in profit post-bath than their matching firms. Additionally, the volatility of their earnings relative to the volatility of their cash flows is smaller and their earnings are more precise.

Our second analysis examines changes in information asymmetry post-bath. We use 11 proxies for information asymmetry. Relative to our matched sample, bath firms see a significant decrease in information asymmetry. Spreads decrease by as much as 11 basis points, turnover increases by 16 basis points per month, monthly return volatility declines by as much as 17 basis points, the standard deviation of analyst earnings estimates decreases by 44 basis points, and the Amihud (2002) and Roll (1984) measures both decline substantially.

Our third analysis measures changes in earnings responsiveness following baths. While the average earnings response coefficient (ERC) for our sample is 0.57, the post-bath ERC for bath firms is 0.14 higher, consistent with such firms' stock prices being more responsive to unexpected earnings in the period following a bath. Taken together, these results show that post-bath earnings are smoother and more informative for bath firms, supportive of the transparency hypothesis.

Having found evidence that baths "clear the air" relative to non-bath matching firms, we divide the bath sample into voluntary and forced baths using the balance sheet constraint measure of Barton and Simko (2002). Both subsamples show an improvement in the information environment post-bath relative to their matching firms, but the improvement is more pronounced for the forced bath subsample. This evidence is consistent with pre-bath managerial obfuscation in the forced bath subsample, a conclusion reinforced by the weaker corporate governance of the forced bath subsample firms.

Our study contributes to the literature in a least four ways. First, we add to the bath literature by assessing the long-term consequences of baths. Whereas the bath literature has been predominantly concerned with the causes of baths and short-term market reactions to them, our study examines the informativeness of earnings and information asymmetry for the 3 years following a bath. Second, we contribute to the earnings smoothing literature by providing analysis of a specific empirical event where a change in smoothing impacts the informativeness of earnings. Third, our study adds to the information asymmetry literature by enhancing the understanding of how a major accounting decision influences a firm's information environment. Finally, we provide evidence consistent with bad news being withheld longer in poorly governed firms. When forced to disclose, those firms realize a greater improvement in their information environment than do voluntary disclosers.

2. Relevant literature

"Bath" has become the general term used to describe a large loss, asset write-down, or other non-recurring charge. Moore (1973) finds that new managers use their discretion to minimize current income.[1] He argues that "taking a bath" alters the benchmark for future comparisons and increases future earnings by removing future losses from future income statements. Analyzing accounting decisions in light of bonus compensation contracts, Healy (1985) proposes a theory of bath accounting. He argues that managers select accounting practices (e.g., use managerial discretion to ensure income before taxes exceeds a set amount) to trigger the payment of managerial bonuses. In this setting, if no accounting maneuvers can ensure a bonus is paid in the current period, managers have an incentive to accelerate write-offs, maximize realized losses, and defer income. This action has two direct effects. First, current net income is reduced. Second, future net income is inflated relative to the income that would have been reported without the write-offs.

Although the study of the causes of baths is important, there are also important reasons to study the consequences of baths. Writing off an asset (a write-off) when the abandonment value exceeds the present value of all subsequent future cash flows is a simple decision for a manager, as it does not require discretion (Gaumnitz and Emery, 1980). However, as discussed by Strong and Meyer (1987), it is more difficult to determine an accurate residual value or correctly identify an incremental decline in an asset's value (a write-down). If the asset is actually sold for more than its residual value, the excess is credited back to income. Strong and Meyer (1987), basing their analysis on the incentive for managers to maximize write-downs in order to maximize future income, find evidence of excessive write-downs following managerial turnover or poor firm performance.

[1] The idea that managers use unique events to justify baths is also discussed by Bernstein (1970) in the context of mergers and reserves for future costs and losses.

Following Healy (1985), bath accounting practices have been considered distinct from earnings smoothing (Dye, 1988; Trueman and Titman, 1988; Fudenberg and Tirole, 1995). Kirschenheiter and Melumad (2002) link the two concepts, proposing a model of the inferred precision of long-term earnings. As investors cannot know either a firm's true long-term earnings or the precision of announced earnings, they must infer the accuracy of reported earnings over multiple periods. Managers, therefore, have an incentive to underreport positive earnings surprises (smoothing) to save income for future periods and to increase the inferred precision of earnings announcements. However, when faced with large negative earnings surprises, managers have an incentive to introduce additional noise into the announcement by maximizing losses through taking a bath. The bath both produces noise that reduces the inferred precision of the announcement and preserves discretionary income for future smoothing.

The ambiguity of the relation between earnings smoothing and the quality of earnings is discussed by Dechow and Skinner (2000).[2] Accruals-based accounting, designed to create more economically meaningful earnings by intertemporally matching revenues and expenses, mechanically smoothes earnings. By construction, these smoothed earnings can convey more information to outsiders than non-smoothed cash-based earnings by stripping away transient cash flows, matching revenues to expenses, and making earnings more persistent.[3] However, the flexibility of accruals-based accounting can also result in excess earnings smoothing.

Some studies suggest that earnings smoothing improves the quality of earnings. Trueman and Titman (1988) propose a model in which high quality firms smooth earnings as a signal of low risk by demonstrating less volatile revenue. Chaney and Lewis (1995) report evidence supportive of this model. Verrecchia (1986) argues that the balance between agency conflict and compensation can benefit shareholders by encouraging managers to produce earnings with less noise on a consistent basis under appropriate compensation contracts. Subramanyam (1996) finds that managers use discretionary accruals to smooth earnings, and that those smoothed earnings are more economically representative of future earnings. Affleck-Graves et al. (2002) find that firms with more predictable earnings have lower spreads, suggesting lower information asymmetry. Tucker and Zarowin (2006) find that firms with smoother earnings have more earnings information incorporated into returns than those with less smooth earnings.

Conversely, there is also theoretical and empirical evidence suggesting that earnings smoothing degrades the informativeness of earnings. Several theories have been proposed based on agency conflicts that motivate managers to obscure true earnings in order either to ensure bonus compensation or to retain their jobs (Lambert, 1984; Dye, 1988; Stein, 1989). These theories are empirically supported by studies that find that managers with performance compensation incentives or firms with weak corporate governance actively smooth earnings (Healy, 1985; Skinner, 1993; DeFond and Park, 1997; Leuz et al., 2003). The result of agency-motivated smoothing (often referred to as earnings manipulation) is usually interpreted as degrading the quality of a firm's earnings and increasing information asymmetry (Bhattacharya et al., 2003; Leuz et al., 2003; Huang et al., 2009).

An important consequence of imperfect disclosure is information asymmetry. Information asymmetry imposes costs on firms and investors. For example, information asymmetry might be a priced risk factor (Easley et al., 2002; Duarte and Young, 2009; Hwang and Qian, 2010), can impact a firm's cost of equity (Botosan et al., 2004), and influence investor trading costs (Krinsky and Lee, 1996; Huang and Stoll, 1997). These costs further motivate the study of accounting decisions that impact a firm's information environment.

3. Data and methods

There are multiple bath definitions in the literature. Several studies limit their samples to announced asset write-downs (Strong and Meyer, 1987; Zucca and Campbell, 1992; Francis et al., 1996). This approach has several weaknesses. First, limiting the sample to specific write-downs large enough to warrant announced disclosure ignores multiple small write-downs that do not individually justify disclosure but, in combination, are as substantial as a single write-down. Second, managers have other options for artificially lowering income, such as litigation losses/reserves, allowances for facilities construction, and non-recurring expenses (e.g., relocation costs and purchases of research and development). Exclusion of these income statement items artificially narrows the sample of baths analyzed.

We adopt the definition used by Elliott and Shaw (1988) and classify a bath as any fiscal year-end observation in Compustat for which Special Items (SPI) is negative and exceeds one percent of lagged firm total assets.[4] This definition allows us to use the full time series of the Compustat database and provides an objective measure of bath events. Several firms take multiple baths during our sample period. Between 1963 and 2011, we identify three firms with 18 baths each. In order to cleanly analyze changes in firms pre- and post-bath, we need to examine baths that occur in relative isolation. We

[2] See Dechow et al. (2010) for a similar discussion. Demski (1998) develops a model that finds that, dependent on the conditions, earnings smoothing by managers can produce either less informative or more informative earnings. Empirically, Jayaraman (2008) finds that spreads and PIN increase when earnings are smoothed either more or less than cash flows, implying both over smoothing and under smoothing harm the informativeness of earnings.

[3] Kirschenheiter and Melumad (2002, 2004) contend that earnings smoothed by informed managers have higher inferred precision, allowing investors to extract more information from them.

[4] Elliott and Shaw (1988) remove asset write-downs they determine to be non-discretionary. For our sample, we include all special item observations. As discussed in Kirschenheiter and Melumad (2002), baths coincide with non-discretionary negative events. Separating out discretionary and non-discretionary charges could exclude situations where managers take advantage of non-discretionary events. Also, manual deletion of observations induces subjectivity into sample selection, whereas leaving potentially non-discretionary items in our sample biases against our findings (that is, there is no *a priori* reason to believe non-discretionary charges facilitate future earnings management).

therefore eliminate baths that occur within 3 years of another bath (either before or after). We remove baths that are either extreme outliers or data errors (exceed 100 percent of total assets), firms that have total assets less than five million dollars, and financial firms (SIC codes between 6000 and 6199). Finally, to allow for 3 years of data before and after each bath, we remove baths that occur before 1965 or after 2008. These filters leave us with 7,149 firm-bath observations.

3.1. Matching sample

When examining changes in firm characteristics around bath events, it is important to control for the impact of non-bath events. For instance, baths are preceded by negative firm performance; negative stock returns, low/negative income, and increasing book-to-market are common as much as 3 years pre-bath. It is possible that changes in earnings smoothing and earnings informativeness post-bath are common among all firms with poor performance records. We therefore use a matched sample of firms with characteristics (including poor prior performance) similar to those in our bath sample.

We match bath firms to non-bath firms using propensity score matching. We generate a propensity score for each firm each year by regressing a bath indicator variable on firm characteristics found by Francis et al. (1996) to be significant predictors of baths: total assets, book-to-market, income, revenue, cumulative stock returns, and industry classification, as well as two proxies for firm equity liquidity (Amihud (2002) and monthly share turnover). We match each bath firm to a non-bath firm by identifying the non-bath firm with the same fiscal year end with the closest propensity

Table 1
Sample summary statistics.

We identify baths as all reductions in special items in excess of 1% of the prior year's total assets as reported in Compustat. We exclude baths from the sample if firms have lagged total assets below $5 million or another bath occurs within 3 years (before or after). We match bath firms to control firms through a propensity score estimated using logistic regression. We regress a bath indicator variable (0,1) on determinants of baths (Francis et al., 1996), including total assets, book-to-market, income, revenue, cumulative stock returns, and common equity liquidity (Amihud, Roll, and share volume turnover) annually. We match bath firms to control firms with the closest probability of taking a bath in the same year. We report assets and market capitalization in millions. We report special items as a percent of lagged total assets. Panel A reports goodness-of-fit information for our bath prediction model. The left side of the panel reports the coefficients, p-values, and pseudo R^2 for a pooled regression using our entire sample period (1965 through 2006). The right side of the panel reports the time series average coefficients of annual logistic regressions. We report the simple time series average of coefficients, the percent of those coefficients that are positive, and the p-value of the average z-score statistic (assuming the annual estimations are independent of each other), aggregate z-score is the sum of annual z-scores divided by the square root of the number of years in our sample (Armstrong et al., 2010). Panel B reports a summary of firm characteristics of our bath and matched firms both in the year prior to the bath (matching variables) and the year of the bath (bath year). p-Value is the p-value associated with a t-test of the difference in the characteristic between the bath and matched sample. K-S is the p-value associated with the non-parametric Kolmogorov-Smirnov distributional test for a difference between the bath and matched samples. ***, **, and * denote statistical significance at the 1, 5, and 10 percent confidence levels respectively.

Panel A	Pooled		Annual		
	Coef.	p-Value	Avg. coef.	Percent positive	Agg. p-Value
Intercept	−2.79	<0.01	−3.12	0%	<0.01
Log(Assets$_{t-1}$)	−0.04	<0.01	−0.04	39.02%	<0.01
B/M$_{t-1}$	0.01	0.95	−30.03	17.08%	<0.01
Revenue$_{t-1}$	−0.01	<0.01	−0.14	41.46%	<0.01
Income$_{t-1}$	−0.32	0.66	−1.12	56.10%	<0.01
Return$_{t-1}$	−0.77	<0.01	−1.27	0%	<0.01
Amihud$_{t-1}$	0.01	0.01	−378,035	65.85%	<0.01
Turnover$_{t-1}$	0.05	0.03	0.77	68.29%	<0.01
Pseudo R^2	0.0238				

Panel B	Bath firms	Matched firms	p-Value	K-S
Matching variables				
Assets$_{t-1}$	$1,319	$1,322	0.98	0.02
B/M$_{t-1}$	0.36	0.17	0.06	<0.01
Revenue$_{t-1}$	115%	119%	0.04	<0.01
Income$_{t-1}$	−0.89%	−0.45%	0.31	<0.01
Return$_{t-1}$	−2.22%	1.33%	<0.01	<0.01
Amihud$_{t-1}$	5.40	4.89	0.47	0.23
Turnover$_{t-1}$	10.15%	9.95%	0.52	<0.01
Propensity score	6.79%	6.31%	<0.01	<0.01
Bath year				
Events	5,546	5,546		
Assets$_t$	1,482	1,474	0.96	0.25
Mktcap$_t$	942	905	0.76	0.01
Income$_t$	−12.22%	0.08%	<0.01	<0.01
Special Items$_t$	−8.00%	0.55%	<0.01	<0.01
Debt/Equity$_t$	1.37	2.00	0.16	<0.01

score. As the matching procedure requires complete data for the prior year, as well as a non-bath firm with the same fiscal year end, we are unable to match all baths. Our final matching sample consists of 5,546 baths and 5,546 matching non-baths.

Panel A of Table 1 reports relevant statistics from the logistic regressions we use to generate propensity scores. Pooled regressions show that several firm characteristics are significantly related to baths. Assets, revenue, and return are all negatively related to bath behavior. Liquidity has a mixed relation with baths.[5] To generate *p*-scores for matching, we run the same logistic regression annually. Panel A also reports the time series average of these cross-sectional coefficients. The annual cross-sectional regressions produce the same predicted relations as the pooled model, though the coefficient on *Amihud* reverses. Additionally, we find all seven independent variables to be significantly related to baths.[6]

We report summary statistics for the bath and match samples in Panel B of Table 1. There is considerable similarity between bath and non-bath firms. The top half of Panel B lists the cross-sectional means of the lagged firm characteristics on which the firms are matched. We are able to closely match firms on assets, income, and liquidity (*Amihud* and *Turnover*). However, our matching firms have lower book-to-market values than bath firms, higher revenues, and higher stock returns. Turning to the year of the bath, the bottom half of Panel B, we observe some differences between bath and non-bath firms. Non-bath firms have net income of 0.08 percent and special items of 0.55 percent of lagged assets. Bath firms have net income of −12.22 percent. Negative special items (−8.00 percent of lagged assets) explain a large portion of the lower bath firm earnings.[7]

3.2. Earnings smoothing, precision, and responsiveness

Because there is no universally accepted metric for earnings smoothing, we use five widely accepted smoothing proxies. *Smooth*(*std*) is defined as the standard deviation of earnings divided by the standard deviation of cash flows (Dechow et al., 2010), each over the 3 years before and the 3 years after a bath.[8] *Smooth*(*var*) is defined as the variance of earnings minus the variance of cash flows (Jayaraman, 2008), each over the 3 years before and the 3 years after a bath. *Small Positive* is defined as an indicator variable equal to 1 if a firm has income before extraordinary items between 0 and 5 percent of lagged total assets and 0 otherwise. *Small Increase* is defined as an indicator variable equal to 1 if a firm has an increase in income before extraordinary items between 0 and 1.3 percent of lagged total assets and 0 otherwise (Burgstahler and Dichev, 1997; DeGeorge et al., 1999).[9] Following Gow et al. (2011), we define *Precision* as the variance of earnings before extraordinary items scaled by lagged total assets over the prior 3 years.[10]

In addition to smoothing, we also examine the responsiveness of firm abnormal stock returns to unexpected earnings pre- and post-bath. We measure abnormal returns in excess of the market return using the market model:

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{it} \tag{1}$$

where $R_{i,t}$ is firm *i*'s stock return in excess of the risk free rate on day *t* and $R_{m,t}$ is the market return in excess of the risk-free rate. We estimate β_i using OLS and the prior 12 months of daily stock returns and measure daily abnormal returns as $R_{i,t} - \beta_i R_{m,t}$. We estimate unexpected earnings from quarterly Compustat data as

$$UE_{i,t} = \frac{A_{i,t} - F_{i,t}}{P_{i,t}} \tag{2}$$

where $A_{i,t}$ is the actual quarterly reported earnings per share, $F_{i,t}$ is the mean forecasted earnings per share as reported in the Institutional Brokers' Estimate System (I/B/E/S) database, and $P_{i,t}$ is the stock's price at the close of trading at the end of the prior month. We measure earnings responsiveness by regressing the cumulative abnormal return for the 3 days surrounding the earnings announcement ($t-1$ through $t+1$) on unexpected earnings.[11]

[5] The pseudo R^2 for our pooled logistic regression is 0.0238. This R^2 is similar to that of Francis et al. (1996) who, when examining discretionary write-downs, find an R^2 of 0.049. The idiosyncratic nature of write-downs creates difficulty in identifying an ideal matched sample, an inherent limitation of the study.

[6] Our evaluation of the statistical significance of our match is in accordance with Armstrong et al. (2010).

[7] We evaluated additional firm characteristics for identifying a matched sample. These include share price, spreads, analyst coverage, earnings smoothing, earnings responsiveness, return on assets, industry characteristics, and indicators variables for earnings surprises. The specification presented here is the one that provides the best statistical fit as well as the closest bath year firm characteristic match. Our empirical results are robust to the inclusion of these additional matching characteristics.

[8] Cash flow from operations is reported directly in Compustat starting in 1987. For observations prior to 1987, we calculate cash flows in accordance with Bowen et al. (1987). We also conduct our analyses using only post-1986 data and find similar results.

[9] Each of the smoothing and precision measures is Winsorized at the 1st and 99th percentiles.

[10] Gow et al. (2011) define earnings precision as the variance of earnings over the prior 10 years. However, given our need to not overlap with prior baths, we are restricted to using only 3 years of earnings. Ng (2011) uses a 5-year window to calculate earnings precision. If we use 4 or 5 years of earnings to calculate precision we find qualitatively similar results. Also, Gow et al. (2011) scale earnings by other variables (market capitalization, shares outstanding, total assets). We choose lagged total assets to match our precision measure with our smoothing measures, which are also scaled by lagged total assets. If we deflate earnings by market capitalization or shares outstanding, we find similar results.

[11] For papers using a similar basic definition of earnings responsiveness, see Imhoff and Lobo (1992), Collins and Kothari (1989), and Kothari and Sloan (1992).

3.3. Information asymmetry

We use 11 measures of information asymmetry. We calculate seven market-based measures using data from the CRSP daily file, monthly for 1962 through 2011. We define *Turnover* as monthly volume divided by shares outstanding. *Daily Spread* is the monthly mean of the daily high/closing ask price minus the low/closing bid price reported in CRSP. *HL spread* is the bid-ask spread component of the decomposition of daily spread into volatility and bid-ask spread components in accordance with Corwin and Schultz (2012). *Roll* is the Roll (1984) covariance measure defined as $2 \times \sqrt{-Cov(\Delta p_{i,t}, \Delta p_{i,t-1})}$, where Δp_t is the change in log price from end of day $t-1$ until the end of day t, set to zero if the covariance is positive. *Amihud* is the monthly mean daily price impact measure proposed by Amihud (2002) and defined as $|Return_{i,t}|/Dollar\ Volume_{i,t}$, where $Dollar\ Volume_{i,t}$ is in millions of dollars. *Realized Volatility* is the monthly sum of daily squared returns (French et al., 1987; Andersen et al., 2001). *Return Standard Deviation* is the monthly standard deviation of daily returns.

We use two analyst-based measures obtained from the I/B/E/S data for 1976 through 2011. *Analyst Standard Deviation* is the standard deviation of all current one-year-ahead earnings forecasts. *Number of Analysts* is the number of analysts in I/B/E/S with outstanding issued trading recommendations.

Finally, we use two transaction-level measures calculated for years 1993 through 2011 from the Trade and Quote (TAQ) database. *Effective Spread* is the monthly trade dollar volume weighted mean of the transaction level calculation of $2\,|\ln(Price)_{i,\tau} - \ln(Mid_{i,\tau})|$ (Goyenko et al., 2009). *Quoted Spread* is the monthly trade dollar volume weighted mean of the transaction level calculation of $(Ask_{i,\tau} - Bid_{i,\tau})/Mid_{i,\tau}$.[12] To mitigate the impact of extreme tails, we Winsorize all measures at the 1st and 99th percentiles.

3.4. Difference-in-differences analysis

We use a regression specification that identifies the differences in pre- and post-bath changes between bath and non-bath firms. The specification focuses on three indicator variables. *Bath Firm* is equal to 1 for all bath firms and 0 for all matching (non-bath) firms. *Post-bath Period* is equal to 1 for all observations that occur after the bath (or in the case of non-bath firms, after the matching firm's bath) and zero otherwise. Finally, *Bath Firm*Post-bath Period* is the interaction of the *Bath Firm* and *Post-bath Period* indicator variables. Regressing firm characteristics on these three indicator variables provides a comprehensive picture of bath firms' characteristics and how they change around baths, both in absolute terms and relative to matched firms. The coefficient on *Bath Firm* illustrates differences, on average, between bath and non-bath firms. The coefficient on *Post-bath Period* identifies the change in the variable of interest following the bath for all firms (both bath and non-bath). In the result most important to this study, the coefficient on the interaction of those two indicator variables (*Bath Firm*Post-bath Period*) shows the change in the variable of interest post-bath for bath firms in relation to non-bath firms. All regressions use panel OLS with standard errors clustered by time to estimate *t*-statistics.

3.5. Forced versus voluntary baths

The actual degree of discretion in the decision to take a bath varies across firms. Some managers will hoard bad news until the magnitude of such news is so great that it can no longer be withheld. Other managers will release such information earlier. We refer to the former as forced baths and the latter as voluntary baths. We explore whether the consequences of a bath differ across these two subsamples.[13] We use the approach of Barton and Simko (2002), who find that managers' ability to bias earnings is constrained when net operating assets are overstated, to identify forced and voluntary baths. We use their measure to create an indicator to identify bath firms for which net operating assets are overstated relative to what they would be under a neutral GAAP application. We take the cross-sectional median of this proxy annually for all firms in COMPUSTAT and designate all firms in the sample with above the median as forced (indicator=1) and those below the mean as voluntary. Under this definition, 45.69% of our sample baths are forced.

4. Findings

4.1. Smoothing

The first stage of our analysis is designed to uncover how earnings change following baths. We examine the change in several annual accounting measures both pre- and post-bath for bath and non-bath firms. Table 2 presents the results of this analysis. A significant estimated regression coefficient on *Bath Firm*Post-bath Period*, the interaction of the bath firm indicator and the post-bath indicator, points to a significant change in the dependent variable for bath firms in the post-bath period over and above that experienced by non-bath matching firms.

[12] In accordance with Chordia et al. (2000), we filter transactions by discarding trades with a bid-ask spread greater than five dollars, and effective-to-quoted spread ratio greater than four, or a quoted proportional spread greater than 40 percent.

[13] We thank the referee for suggesting this line of inquiry.

Table 2
Accounting changes.

We gather accounting data for the 3 fiscal years prior to the bath and the 3 years following the bath. We regress each variable on three indicator variables:

$$Depvar_{i,t} = \alpha_i + \beta_1 \text{ Bath Firm}_i * Post-bath\ Period_t + \beta_2 \text{ Bath Firm}_i + \beta_3 \text{ Post}-bath\ Period_t + \varepsilon_{i,t}$$

where *Bath Firm* equals 1 if the firm has a bath and 0 if the firm is in the control sample, *Post-bath Period* equals 1 for all observations that occur after the bath and 0 otherwise, and *Bath Firm Post-bath Period* is the interaction of these two indicator variables. We cluster all standard errors by year.

Net Income is net income before extraordinary items divided by lagged total assets. *Debt/Equity* is total liabilities divided by total assets minus total liabilities. *Precision* is the variance of earnings before extraordinary items scaled by lagged total assets over the prior 3 years (Gow et al., 2011). *Smooth(std)* is the standard deviation of income before extraordinary items divided by the standard deviation of cash flows from operations (Dechow et al., 2010), each over 3 years (pre- and post-bath). *Smooth(var)* is the variance of income before extraordinary items divided by the variance of cash flows from operations (Jayaraman, 2008), each over 3 years (pre- and post-bath). *Small profit* is an indicator variable equal to 1 if a firm has income before extraordinary items between 0 and 5 percent of lagged total assets. *Small increase* is an indicator variable equal to 1 if a firm has an increase in income before extraordinary items between 0 and 1.3 percent (Burgstahler and Dichev, 1997; Degeorge et al., 1999). We measure *Net income*, *Debt/Equity*, *Small Increase*, and *Small Profit* annually. We measure *Smooth(std)*, *Smooth(var)*, and *Precision* once pre-bath and once post-bath. We multiply all coefficients by 100 and report them as percentages.

	Bath Firm *Post-bath Period	Bath Firm	Post-bath period	N	Adj. R^2
Net income	4.19	−1.59	5.35	55,493	1.63%
	5.18	*−2.80*	*5.29*		
Debt/equity	0.02	−0.10	0.07	50,356	0.04%
	0.35	*−2.34*	*1.87*		
Small increase	1.28	−0.60	−0.10	46,503	0.05%
	2.21	*−0.85*	*−1.26*		
Small profit	1.18	1.37	1.76	55,493	1.26%
	1.68	*3.40*	*2.85*		
Smooth(std)	−6.93	−3.07	−13.47	18,885	0.13%
	−1.70	*−0.94*	*−3.57*		
Smooth(var)	−1.69	1.61	−2.75	18,885	0.18%
	−1.78	*1.54*	*−2.69*		
Precision	−0.05	0.05	−0.04	18,885	0.08%
	−1.55	*1.05*	*−2.40*		

All firms, bath and matching, experience an increase in *Net Income* in the post-bath period (5.35 percent). Although bath firms on average (both pre- and post-bath) have lower net income (by 1.59%), they see an additional increase in net income relative to matching firms of 4.19% in the post-bath period. This finding, in and of itself, does not imply that a bath is a positive event for the firm. Increased post-bath earnings could be either informative (transparent) or uninformative (opaque). We examine *Debt/Equity* to verify that our information asymmetry results in the following section are not driven by changes in leverage. We find no significant relative change in *Debt/Equity* for bath firms post bath.

The remainder of Table 2 examines the five proxies for smoothing. A statistically greater proportion of bath firms report a *Small profit* in the post-bath period than do non-bath firms. *Smooth(std)* and *Smooth(var)* are also significantly different for bath firms in the post-bath period, and in the direction consistent with greater smoothing after a bath. At varying levels of significance, the *Bath Firm*Post-bath Period* coefficients indicate greater earnings smoothing for bath firms than for matching firms in the post-bath period. We conclude from the evidence in Table 2 that bath firms have smoother earnings post-bath than they do pre-bath, and have smoother earnings than similar non-bath firms.

4.2. Information asymmetry

The presence of smoother earnings post-bath does not necessarily imply increased or decreased information content of those earnings (Dechow and Skinner, 2000). Therefore, we structure the second stage of our analysis to detect differences in information asymmetry pre- and post-bath, with the goal of distinguishing between the transparency and obfuscation hypotheses. Table 3 presents the results of this analysis. We examine 11 proxies for information asymmetry using the same regression model as in Table 2.[14]

We find evidence consistent with a change in information asymmetry for all firms. Ten of 11 information asymmetry proxies increase significantly in the post-bath period for bath and non-bath firms alike. To illustrate, we observe increases in *Realized Volatility* by 54 basis points, *Quoted Spread* by 13 basis points, and the standard deviation of analyst earnings forecasts by 30 basis points. The magnitude of these changes is large in comparison to our sample's pre-bath mean *Realized Volatility* of 3.85 percent, *Quoted Spread* of 2.46 percent, and *Analyst Standard Deviation* of 3.35 percent. These (untabulated)

[14] Our results are qualitatively similar with the inclusion of fixed effects or when clustering by firm.

Table 3
Information asymmetry.
We estimate monthly proxies of information asymmetry for the 36 months prior to and the 36 months following a bath. We then regress these monthly proxies on three indicator variables and controls as follows:

$$IA_{i,t} = \alpha_i + \beta_1\ Bath\ Firm_i\ *Post-bath\ Period_t + \beta_2\ Bath\ Firm_i + \beta_3\ \ Post-bath\ Period_t\ + \delta\ \ Controls_{i,t} + \varepsilon_{i,t}$$

where *Bath Firm* equals 1 if the firm has a bath and 0 if the firm is in the control sample, *Post-bath Period* equals 1 for all observations that occur after the bath and 0 otherwise, and *Bath Firm*Post-bath Period* is the interaction of the two other indicator variables. We include total assets, book-to-market, debt-to-equity and income scaled by lagged total assets as controls. We cluster all standard errors by year. We do not report coefficients on controls.
We define *Turnover* as monthly volume divided by shares outstanding. We measure *Daily Spread* monthly as the mean daily difference between the day's high and low trading/quote price divided by closing price. *HL Spread* is the monthly mean of daily estimated effective spread calculated in accordance with Corwin and Schultz (2012). *Roll* is the monthly estimated spread estimated by the daily covariance in prices calculated in accordance with Roll (1984). *Amihud* is the monthly mean of daily dollar volume price impact, defined as daily return divided by daily dollar volume, calculated in accordance with Amihud (2002). *Realized Volatility* is the monthly sum of squared daily returns. *Standard Deviation* is the monthly standard deviation of daily returns. *Analyst Standard Deviation* is the standard deviation of analyst one-year-ahead earnings estimates as reported in I/B/E/S. *Number of Analysts* is the number of analysts that have outstanding issued trading recommendations. *Effective Spread* is the dollar volume weighted mean effective spread, defined as two times the absolute difference in logged price and logged midpoint, of all transactions recorded in TAQ during that month. *Quoted Spread* is the dollar volume weighted mean quoted spread, defined as the difference between the quoted ask and bid prices divided by trade price, of all transactions recorded in TAQ during that month.

	Bath Firm *Post-bath Period	Bath Firm	Post-bath period	*N*	Adj. R^2
Turnover	0.16	−0.17	1.13	753,738	5.72%
	2.71	*−5.44*	*8.44*		
Daily Spread	−0.18	0.14	0.19	753,738	6.88%
	−8.28	*8.70*	*5.52*		
HL Spread	−0.03	0.07	−0.05	753,738	1.97%
	−2.20	*4.99*	*−2.08*		
Roll	−0.08	0.02	0.09	753,738	3.28%
	−7.08	*3.61*	*6.95*		
Amihud	−0.23	0.16	0.37	753,738	1.13%
	−4.36	*5.17*	*5.72*		
Realized Volatility	−0.32	0.20	0.54	753,738	6.58%
	−7.12	*8.22*	*8.82*		
Return Stdev	−0.17	0.09	0.17	753,738	8.71%
	−9.47	*9.22*	*7.03*		
Analyst Stdev	−0.44	0.54	0.30	690,704	0.89%
	−6.85	*12.11*	*6.51*		
# Analysts	−0.02	0.11	0.13	690,704	10.47%
	−0.69	*6.54*	*4.46*		
Effective Spread	−0.10	0.17	0.08	443,628	2.78%
	−8.36	*17.39*	*3.52*		
Quoted Spread	−0.11	0.24	0.13	443,628	2.41%
	−6.85	*18.27*	*4.31*		

results are consistent with firms experiencing poor operating performance that might lead to a bath have a statistically and economically significant degradation in their information environment, in contrast to the overall market trend of decreasing information asymmetry over the same period (Chordia et al., 2008).

However, tests of the transparency hypothesis center on the changes in bath firms relative to their matching firms. We thus turn to the estimated coefficient on *Bath Firm*Post-bath Period*, the interaction of *Bath Firm* and *Post-bath Period*. We find evidence consistent with decreasing information asymmetry for bath firms in the post-bath period compared to matching firms for 10 of the 11 information asymmetry proxies. *Turnover* increases by 16 basis points per month for bath firms in the post-bath period compared to non-bath firms. An increase in *Turnover* is consistent with a decrease in information asymmetry (Chae, 2005).

Measures of spread decrease for bath firms in the post-bath period compared to non-bath firms. *Quoted Spread* decreases by 11 basis points for bath firms in the post-bath period compared to non-bath firms. Bath firms in the post-bath period experience significant reductions in *Effective Spread* and the *Roll* measure relative to non-bath firms. Spreads tend to be greater during instances of increased information asymmetry between traders, as market makers seek to protect themselves against informed traders with higher bid-ask spreads. The results are consistent with lower information asymmetry in the market for bath firms' equity post-bath compared to the non-bath matching firms.

Table 4
Earnings responsiveness.
The regression of three day cumulative abnormal returns ($CAR_{t-1,t+1}$) on unexpected earnings (*UE*) and two indicator variables, bath firms (*Bath Firm*), post-bath (*Post-bath Period*), and the interaction of the two (*Bath Firm*Post-bath Period*). We define unexpected earnings as reported quarterly earnings in excess of median analyst estimates during the 60 days prior to announcement.

	Coefficient	*t*-Statistic
UE	0.57	*2.07*
UE *Bath Firm *Post-bath Period	0.14	*1.89*
UE *Bath Firm	0.61	*2.14*
UE *Post-bath Period	0.27	*0.92*
Bath Firm *Post-bath Period	0.02	*0.98*
Bath Firm	−0.02	*−1.26*
Post-bath Period	0.02	*0.95*
N	79,821	
Adj R^2	0.14%	

Both proxies related to return volatility decrease for bath firms in the post-bath period compared to matching firms, consistent with a relative decrease in information asymmetry (Benston and Hagerman, 1974; Chordia et al., 2001). The *Amihud* price impact measure also decreases for bath firms in the post-bath period compared to non-bath firms. Information asymmetry is positively related to this measure, as trades have a higher impact on stock price in the absence of other information. Finally, *Analyst Standard Deviation* is lower for bath firms in the post-bath period compared to non-bath firms. Analyst estimates exhibit lower dispersion when information about a firm is more abundant (Kothari et al., 2009a). The results we present in Table 3 are consistent with taking a bath resulting in decreased information asymmetry compared to similar firms that choose not to take a bath. Our findings suggest that the (smoother) post-bath earnings shown in Table 2 convey more information than pre-bath earnings, and thus our results are consistent with the transparency hypothesis.

4.3. *Stock price responsiveness to unexpected earnings*

We next examine how baths impact the responsiveness of the firm's stock price to unexpected earnings. Although we interpret decreased information asymmetry as evidence that smoother post-bath earnings are more informative, a change in earnings responsiveness provides additional evidence of post-bath informativeness. We regress the cumulative abnormal return (CAR) for the stock from the day before the earnings announcement to the day following the announcement on unexpected earnings, the three indicators present in our previous regressions, and the interaction of these three indicators with unexpected earnings. Table 4 presents the results.

If bath firms' stock prices are more sensitive to unexpected earnings in the period following a bath, the interaction of unexpected earnings, the bath sample indicator, and the post-bath period indicator will have a positive and significant estimated coefficient. We find that the earnings response coefficient (ERC) increases by 0.14 (t=1.89) for bath firms after a bath, compared to a baseline ERC of 0.57 for the entire sample. A bath improves stock price responsiveness to unexpected earnings, which is consistent with such earnings being more informative. The greater informativeness of earnings post-bath is supportive of the transparency hypothesis.

Increased earnings response coefficients for bath firms post-bath suggest that the improvement in the information environment of the bath firm is attributable, at least in part, to greater transparency. To further examine this possible avenue of decreased information asymmetry, we break down our 3-year post-bath period into three separate years, each of which is represented by its own indicator variable. If the post-bath reduction in information asymmetry is directly attributable to the bath itself, then we would expect the change in our information asymmetry proxies to occur predominantly in the year following the bath. However, if the bath event improves the quality of future disclosures, we would also expect a reduction in information asymmetry to occur in the second and third years following the bath.

Table 5 reports the results of this difference-in-difference decomposition for each of the 3 years following a bath. The results are consistent with improved future disclosure improving the firm's information environment. Examining *Turnover*, we find that monthly turnover actually decreases by 51 basis points in the year following a bath. It then increases by 22 basis points the second year, followed by a 90 basis point increase in the third year relative to the non-bath matching sample. This pattern suggests that information asymmetry actually increases immediately following a bath, but improves over time. Our five spread proxies (*Daily Spread*, *HL Spread*, *Roll*, *Effective spread*, and *Quoted Spread*) see either increases or economically small decreases in the first post-bath year. However, all five exhibit statistically and economically significant decreases in the third year, consistent with a reduction in information asymmetry. For example, *Effective Spread* decreases by a substantial 22 basis points in year three. The same pattern is evident in our price impact proxy (*Amihud*), in our volatility measures (*Realized Volatility* and *Return Standard Deviation*), and in *Analyst Standard Deviation*. In all of these cases, the majority of the reduction in information asymmetry occurs in the second and third years following a bath.

Our finding of a delayed reduction in information asymmetry is consistent with prior bath literature. Baths are viewed as negative events by market participants (Elliott and Shaw, 1988; Francis et al., 1996). Negative information takes time for the market to process (Ball and Brown, 1968; Bernard and Thomas, 1990; Francis et al., 2007). Downward price pressure

Table 5
Information asymmetry over time.
We estimate monthly proxies of information asymmetry for the 36 months prior to and the 36 months following a bath. We then regress these monthly proxies on three indicator variables and controls

$$IA_{i,t}=\alpha_i+\beta_1 Year1_t *Bath\ Firm_i+\beta_2 Year2_t *Bath\ Firm_i+\beta_3 Year3_t *Bath\ Firm_i\ +\beta_4 Bath\ Firm_i+\beta_5 Post-bath\ Period_t+\delta Controls_{i,t}+\varepsilon_{i,t}$$

where *Bath Firm* equals 1 if the firm has a bath and 0 if the firm is in the control sample, *Post-bath Period* equals 1 for all observations that occur after the bath and 0 otherwise, Year1 is an indicator equal to 1 for the year following a bath and 0 otherwise, Year2 is an indicator for the second year following a bath, and Year3 is an indicator for the third year following a bath. We include total assets, book-to-market, debt-to-equity and income scaled by lagged total assets as controls. We cluster all standard errors by year. We do not report coefficients on controls.
We define *Turnover* as monthly volume divided by shares outstanding. We measure *Daily Spread* monthly as the mean daily difference between the day's high and low trading/quote price divided by closing price. *HL Spread* is the monthly mean of daily estimated effective spread calculated in accordance with Corwin and Schultz (2012). *Roll* is the monthly estimated spread estimated by the daily covariance in prices calculated in accordance with Roll (1984). *Amihud* is the monthly mean of daily dollar volume price impact, defined as daily return divided by daily dollar volume, calculated in accordance with Amihud (2002). *Realized Volatility* is the monthly sum of squared daily returns. *Return Standard Deviation* is the monthly standard deviation of daily returns. *Analyst Standard Deviation* is the standard deviation of analyst 1-year-ahead earnings estimates as reported in I/B/E/S. *Number of Analysts* is the number of analysts that have outstanding issued trading recommendations. *Effective Spread* is the dollar volume weighted mean effective spread, defined as two times the absolute difference in logged price and logged midpoint, of all transactions recorded in TAQ during that month. *Quoted Spread* is the dollar volume weighted mean quoted spread, defined as the difference between the quoted ask and bid prices divided by trade price, of all transactions recorded in TAQ during that month.

	Year1* Bath Firm	Year2* Bath Firm	Year3* Bath Firm	Bath Firm	Post-bath Period
Turnover	−0.51	0.22	0.90	−0.17	1.13
	−4.28	*2.86*	*7.49*	*−5.40*	*8.44*
Daily spread	−0.10	−0.17	−0.30	0.14	0.19
	−2.71	*−4.89*	*−8.57*	*8.69*	*5.53*
HL spread	0.06	−0.02	−0.16	0.07	−0.05
	2.31	*−0.91*	*−6.46*	*4.98*	*−2.07*
Roll	−0.04	−0.08	−0.12	0.02	0.09
	−2.90	*−6.13*	*−8.55*	*3.60*	*6.96*
Amihud	0.03	−0.18	−0.57	0.16	0.37
	0.46	*−3.25*	*−7.85*	*5.15*	*5.73*
Realized volatility	−0.11	−0.39	−0.49	0.20	0.54
	−1.49	*−6.39*	*−6.63*	*8.20*	*8.83*
Return stdev	−0.09	−0.18	−0.24	0.09	0.17
	−3.73	*−7.82*	*−8.85*	*9.21*	*7.04*
Analyst stdev	−0.03	−0.69	−0.67	0.54	0.30
	−0.34	*−8.78*	*−9.53*	*12.10*	*6.53*
# Analysts	−0.02	−0.04	0.02	0.11	0.13
	−0.72	*−1.15*	*0.55*	*6.54*	*4.46*
Effective spread	0.02	−0.13	−0.22	0.17	0.08
	1.15	*−7.34*	*−13.41*	*17.34*	*3.52*
Quoted spread	0.04	−0.14	−0.25	0.24	0.13
	1.57	*−5.98*	*−10.90*	*18.23*	*4.31*

increases spreads and price impact, while analysts take varying amounts of time to incorporate the substantial financial statement changes associated with baths into their forecasts. Consequently, a firm might not experience a decrease in information asymmetry in the first year following a bath.[15]

4.4. Forced versus voluntary baths

Our prior analyses find strong support for the transparency hypothesis. However, as described above, some baths are substantially at the discretion of management, while others involve much less discretion. Our empirical design takes the

[15] We repeat this analysis separating out the first week, the first month, and the first quarter post bath. In all cases, we find little or no decrease in information asymmetry until the second year following a bath.

Table 6
Forced baths.

We estimate monthly proxies of information asymmetry for the 36 months prior to and the 36 months following a bath. We then regress these monthly proxies on three indicator variables and controls.

$$IA_{i,t} = \alpha_i + \beta_1 Forced_i * Bath\ Firm_i * Post-bath\ Period_t + \beta_2 Forced_i * Bath\ Firm_{i,t} + \beta_3 Forced_i * Post-bath\ Period_t + \beta_4 Forced_i + \beta_5\ Bath\ Firm_i * Post-bath\ Period_t + \beta_6 Bath\ Firm_{i,t} + \beta_7 Post-bath\ Period_{i,t} + \delta Controls_{i,t} + \varepsilon_{i,t}$$

where *Bath Firm* equals 1 if the firm has a bath and 0 if the firm is in the control sample, *Post-bath Period* equals 1 for all observations which occur after the bath and 0 otherwise, and *Bath Firm*Post-bath Period* is the interaction of *Bath Firm* and *Post-bath Period*. We include total assets, book-to-market, debt-to-equity and income scaled by lagged total assets as controls. We cluster all standard errors by year. We do not report coefficients on controls.

Forced is an indicator variable equal to 1 if the firm's net operating assets scaled by sales is above the cross sectional COMPUSTAT median and 0 if below. For brevity, we do no report coefficients and *t*-statistics for control variables.

	Forced *Bath Firm *Post-bath Period	Forced* Bath Firm	Forced* Post-bath Period	Forced	Bath Firm *Post-bath Period	Bath Firm	Post-bath Period
Turnover	0.10	0.26	−0.68	−0.78	0.13	−0.29	1.43
	0.76	*3.03*	*−7.85*	*−10.77*	*1.42*	*−5.55*	*10.82*
Daily spread	−0.15	−0.10	0.22	−0.29	0.18	8.26	0.09
	−3.40	*−4.34*	*6.56*	*−12.74*	*−3.46*	*8.26*	*2.51*
HL spread	−0.12	−0.11	0.24	−0.08	0.02	0.12	−0.15
	−3.66	*−5.52*	*8.85*	*−4.33*	*0.79*	*5.81*	*−7.12*
Roll	−0.04	−0.02	0.04	−0.12	−0.06	0.03	0.07
	−2.56	*−1.58*	*3.37*	*−11.73*	*−4.31*	*3.54*	*4.88*
Amihud	0.03	−0.28	0.16	−0.38	−0.23	0.29	0.29
	0.39	*−4.98*	*2.50*	*−10.45*	*−3.73*	*6.64*	*3.96*
Realized volatility	−0.20	−0.04	0.11	−0.47	−0.22	0.22	0.49
	−2.79	*−0.90*	*2.27*	*−10.06*	*−3.68*	*6.10*	*7.05*
Return stdev	−0.07	−0.01	0.02	−0.23	−0.13	0.09	0.16
	−2.91	*−0.69*	*1.08*	*−12.50*	*−5.91*	*7.46*	*5.94*
Analyst stdev	−0.17	0.31	0.33	0.70	−0.36	0.40	0.15
	−1.67	*4.46*	*4.31*	*12.08*	*−5.93*	*8.18*	*2.67*
# Analysts	−0.05	0.04	0.03	0.07	0.01	0.09	0.12
	−1.41	*1.45*	*0.71*	*2.52*	*0.19*	*5.40*	*3.44*
Effective spread	−0.02	−0.04	0.01	−0.34	−0.09	0.19	0.03
	−0.56	*−1.57*	*4.37*	*−19.36*	*−4.31*	*11.02*	*1.20*
Quoted spread	−0.02	−0.05	0.16	−0.42	−0.10	0.27	0.05
	−0.50	*−1.41*	*5.48*	*−18.59*	*−3.53*	*11.13*	*1.48*

regression specification used in Table 3 and adds an indicator variable identifying the bath subsample:

$$IA_{i,t} = \alpha_i + \beta_1 Forced_i{}^* Bath\ Firm_i{}^* Post - bath\ Period_t + \beta_2 Forced_i{}^* Bath\ Firm_{i,t} + \beta_3 Forced_i{}^* Post - bath\ Period_{i,t} + \beta_4 Forced_i + \beta_5 Bath\ Firm_i{}^* Post - bath\ Period_t + \beta_6 Bath\ Firm_{i,t} + \beta_7 Post - bath\ Period_{i,t} + \delta Controls_{i,t} + \varepsilon_{i,t} \quad (3)$$

where $Forced_i$ identifies firms that have relatively less discretion in reporting by utilizing the Net Operating Asset measure proposed by Barton and Simko (2002). This variable is a measure of balance sheet constraint. The more constrained the balance sheet, the less flexibility managers have in their financial reporting. Baths at firms with constrained balance sheets are likely to represent forced or mandatory baths, while baths at less constrained firms likely represent voluntary baths, consistent with the transparency hypothesis. Table 6 presents the results.

In the post-bath period, *Daily Spread* and *HL Spread* are significantly lower for forced baths than for voluntary baths. Forced baths see a relative decline in *Realized Volatility* and *Return Standard Deviation* of 20 and 7 basis points respectively, while *Analyst Standard Deviation* decreases by 17 basis points. Our interpretation of these results is that firms with constrained balance sheets that are forced to take a bath experience a greater improvement in their information environment than firms that voluntarily choose to take a bath. These findings are consistent with managers withholding bad news for as long as possible and disgorging it only when they have no choice (Kothari et al., 2009b), resulting in larger relative reductions in information asymmetry.

Table 7
Corporate governance of forced and voluntary subsamples.

We identify baths as *Forced* if their net operating assets scaled by sales in the year prior to the bath are above the cross sectional COMPUSTAT median and *Voluntary* otherwise. The table reports governance characteristics of forced and voluntary bath firms. Those firms are then matched to BoardEx using International Security Identification Numbers (ISIN) annually. We measure governance characteristics of bath firms in the year of the bath. *Duality* is an indicator variable equal to 1 if the CEO is also the Chairman of the Board of Directors and 0 otherwise. *Independence* is the percent of board members classified as independent (having no additional financial interest in the firm). *Busyness* is the average number of other boards on which each of the board members sits. *Experience* is the average number of years of experience board members have serving on public firm boards. *Board Size* is the number of directors on the board.

	Voluntary	Forced	*t*-Statistic
Duality	58.44%	54.30%	*1.86*
Independence	61.78%	59.67%	*1.60*
Busyness	2.24	2.37	*−1.65*
Experience	6.77	5.87	*3.18*
Board size	12.59	13.93	*−2.02*
N	1078	919	

Finally, we investigate what might lead a firm to voluntarily take a bath. Using the median Barton and Simko (2002) measure as a cutoff to identify baths as voluntary or forced[16], we examine an array of corporate governance measures from the BoardEx data for both sets of firms to identify differences in corporate governance. Table 7 presents the results. Four of the five measures we examine point to better corporate governance among voluntary bathers. Specifically, these firms have more independent boards, their board members are more experienced and serve on fewer boards, and their boards tend to be smaller. The only measure we examine that points to worse governance for voluntary bathers is Chair/CEO duality, with this situation occurring more frequently at voluntary bathers than at forced bathers. On the whole, this analysis suggests that, with stronger governance, voluntary bathers accumulate less negative information than forced bathers, explaining their smaller post-bath reduction in information asymmetry relative to forced bathers.

5. Summary and conclusions

This paper examines the informativeness of earnings following large non-recurring charges ("baths") to assess the consequences of taking a bath for the firm's information environment. Examining 5,546 baths between 1965 and 2008 using a difference-in-differences analysis, we find substantial evidence in support of the transparency hypothesis, that a bath improves the firm's information environment relative to similar firms that choose not to take a bath. First, we find that earnings become smoother in the 3 years following a bath. All five smoothing proxies suggest smoother earnings post-bath, albeit with varying degrees of significance.

Second, we find that 10 of 11 proxies of information asymmetry are consistent with decreased information asymmetry for bath firms post bath. Changes in turnover, spreads, price impact, and analyst dispersion measures all suggest an increase in public information following baths relative to matching firms. Finally, we measure changes in the responsiveness of stock prices to unexpected earnings. Our bath and matching firms have an average earning response coefficient (ERC) of 0.57. Following baths, we see an increase in ERC among bath firms of 0.14, which suggests that the decrease in information asymmetry following baths is attributable to smoother earnings that are more informative.

Third, we show that firms with balance sheets constrained by prior accounting choices experience a greater relative reduction in information asymmetry following a bath, consistent with a larger amount of information being released by the baths of such firms. These firms' prior accounting choices appear to have created additional information asymmetry in the pre-bath period, an outcome that might be desirable to managers attempting to obscure the poor performance of their firms. The worse corporate governance of these firms appears to allow managers to engage in such pre-bath obfuscation.

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[16] Our results are robust to alternate breakpoints both above and below the median.

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