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THE EFFECTS OF BIG BATHS ON BANK OPACITY

K. Stephen Haggard
Missouri State University

John S. Howe
University of Missouri

Andrew A. Lynch
University of Mississippi

Abstract

Information asymmetry in the banking sector is important to regulators, analysts, and investors. We examine the change in the information environments of banks following large nonrecurring write-downs (baths) and find a reduction in information asymmetry in the three years following a bath. This result is conditional on the type of asset being written down. Loan-related baths result in a permanent decrease in information asymmetry, but merger-related baths are associated with a transitory increase in information asymmetry. Conversely, baths not related to either loans or mergers result in increased opacity. Consistent with a permanent decrease in information asymmetry, we find an increase in earnings responsiveness in the three years following loan-related baths.

JEL Classification: G14, G21, M41

I. Introduction

Outside monitoring of banks is important because banks may pose systemic risks, carrying with them the potential to incapacitate the entire financial system (Calomiris and Gorton 1991; Holod and Peek 2007). However, banks are relatively opaque to outsiders (Morgan 2002), making outside monitoring of banks difficult. As a result, an event that increases or decreases bank opacity is of particular interest to bank regulators, who use financial markets as one tool for monitoring banks. Investors, other stakeholders, and analysts also engage in outside monitoring and thus are also interested in changes in bank opacity.

Haggard, Howe, and Lynch (2015) demonstrate that big baths (large nonrecurring accounting charges) at industrial firms reduce information asymmetry, which they interpret as a decrease in opacity. However, their study does not examine banks. Given the significant differences between banks and industrial firms—greater financial leverage, unique regulations, and opaque assets—we cannot assume that the

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information environments of banks react similarly to baths as the information environments of industrial firms. Furthermore, as Haggard and Howe (2012) demonstrate, different bank assets display differing levels of opacity. Thus, baths involving different types of assets might have differential impacts on the information environments of banks.

In this study, we apply the approach of Haggard, Howe, and Lynch (2015) to examine the impact of big baths on the information environments of banks. We examine provisions for loan losses, net charge-offs, and special items, as the discretionary nature of these accounts suggests they are the most likely to be involved in a large nonrecurring charge at a bank (e.g., Kilic et al. 2013).[1] We use a difference-in-differences approach to examine the change in the information environment of a bathing bank's compared to the change in the information environment of a nonbathing, matching bank.

We find a contrast in how opacity changes following baths between our bath samples. *Loan-related baths* (through provision for loan loss and net charge-offs) result in a reduction in opacity. Following baths, realized volatility, standard deviation of analysts' estimates, and quoted spread decrease by 62, 204, and 50 basis points (bps), respectively. These decreases represent proportional changes of 31.40%, 23.78%, and 14.75% from their prebath levels, which are both statistically and economically significant. Conversely, *special items baths* result in increased opacity. Realized volatility and quoted spread increase by 102 and 49 bps, respectively, representing a 32.38% and 16.01% increase from their prebath levels. The increased opacity is not consistent across all special items baths. Non-merger-related special items (i.e., litigation and fines) baths result in decreased opacity, whereas merger-related special items baths result in increased opacity. For instance, realized volatility increases by 133 bps following merger baths but declines by 118 bps following nonmerger baths. These are both economically significant changes from the 315 bps prebath level of realized volatility.

We also examine changes in bank opacity over time following baths for the different bath samples. We find significant, material changes over time in banks' information environments postbath, with temporal changes in opacity that vary depending on the type of bath. The reduction in information asymmetry following loan-related baths intensifies over the three years following the bath. For instance, realized volatility decreases by 45 bps in the year following the bath, by 63 bps in the second year, and by 85 bps in the third year, suggesting that loan-related baths cause long-term changes in the opacity of banks. However, merger-related baths (through special items related to integration costs or goodwill impairment) result in a transitory increase in bank opacity. Opacity increases the year following such baths, then reverses over the second and third years. For instance, effective spread increases by 85 bps in year 1, decreases by 62 bps in year 2, and decreases a further 201 bps in year 3.

[1] Baths are defined as an increase in provision for loan loss, a negative net charge-off of loans, or a negative special items expense charge greater than 1% of the prior year's assets (Haggard, Howe, and Lynch 2015; Elliott and Shaw 1988). All three items are taken from the Compustat annual file and represent charges to a bank's income statement, each reducing a bank's net income. Specifically, the items used are: change in provision for loan losses (PLL), net charge-offs (NCO), and special items (SPI).

We draw three conclusions from these results. First, bank baths generally result in reduced opacity, specifically following loan-related and immediately following non-merger-related special items baths. Second, merger-related baths substantially increase opacity in the year following the bath. And finally, the permanence of the effect on opacity depends on the type of bath: merger-related bath effects are transient, whereas loan-related baths have a more permanent impact on bank opacity and nonmerger special items baths eventually result in increased opacity.

Our results have important implications for bank regulators, analysts, and investors. We demonstrate that banks undertaking certain types of baths become temporarily more opaque postbath. Bank regulators should consider increasing inspection frequency following baths, as increased opacity reduces the effectiveness of market-based monitoring in the period immediately following the bath. Investors and analysts also benefit from recognizing changes in the opacity of banks. We find that spreads increase the year following merger-related special items baths by as much as 113 bps and as much as 78 bps in the three years following non-merger-related special items baths. The market response to announcements of unexpected earnings becomes stronger following loan-related baths, suggesting that reported earnings contain more information postbath. Of interest to investors, bank opacity affects both expected equity returns (see, e.g., Becht, Bolton, and Roell 2011; Kashyap, Rajan, and Stein 2008; Calomiris and Wilson 2004) and trading costs through greater spreads (Huang and Stoll 1997).

II. Relevant Literature

The literature on baths begins with Moore (1973), who shows that new managers use their accounting discretion to minimize current earnings. Doing so makes achieving future favorable comparisons of earnings easier, as the earnings benchmark for the new manager's tenure is relatively low. Healy (1985) theorizes that managers use their accounting discretion to ensure that bonuses based on accounting thresholds are paid. In the event that achieving a threshold is impossible, managers use their discretion to write down assets and take large accounting charges. This decision in essence pulls losses forward and artificially inflates future reported income, which increases the probability of achieving bonus-triggering accounting thresholds in the future.

Kirschenheiter and Melumad (2002) link the concepts of big baths and earnings smoothing. Earnings smoothing occurs when managers use their accounting discretion to reduce or eliminate quarter-to-quarter fluctuations in net income. The literature is split on whether such smoothing increases information asymmetry (e.g., Lambert 1984; Dye 1988; Stein 1989; Bhattacharya, Daouk, and Welker 2003; Leuz, Nanda, and Wysocki 2003; Huang et al. 2009) or decreases it (e.g., Verrecchia 1986; Trueman and Titman 1988; Chaney and Lewis 1995; Subramanyam 1996; Affleck-Graves, Callahan, and Chipalkatti 2002; Tucker and Zarowin 2006). Haggard, Howe, and Lynch (2015) examine industrial firms and find evidence that big baths reduce information asymmetry, especially "forced" baths at firms with indicators of poor corporate governance.

Another unresolved question in the finance literature concerns the opacity of bank assets. Opaque assets are difficult for outsiders to value and create disagreement about the true value of the firm. Morgan (2002) uses split bond ratings to show that only insurance companies have more opaque assets than banks. Haggard and Howe (2012) use the model of Jin and Myers (2006) to examine the relative opacity of banks. Their results show that banks have less firm-specific information in their equity returns than industrial matching firms, consistent with banks being more opaque than industrial firms. They also show that this opacity is different based on the differences in assets across banks, with agricultural loans and consumer loans being the most transparent. Flannery, Kwan, and Nimalendran (2004) use measures of market microstructure and reach the opposite conclusion, though they amend that opinion in a 2013 paper (Flannery, Kwan, and Nimalendran 2013) to say that banks are more opaque than industrial firms during times of financial crisis.

The literature examining big baths at banks is small, though bank managers have discretion about when to recognize and make provisions for loan losses, giving them wide latitude to take big baths. Fiechter and Meyer (2011) examine U.S. banks during the financial crisis and determine that banks use their discretion in estimating the fair value of nontrading assets to engage in bath behavior. Bornemann, Kick, Pflingsten, and Schertler (2012) show that incoming CEOs engage in bath behavior during their first year at the bank. Neither of these studies examines the impact of bath behavior on the information environments of banks.

III. Data and Methods

We draw the data for our study from several sources. We use daily stock price and volume data from the Center for Research in Security Prices (CRSP), trade-by-trade price data from the Trade and Quote database (TAQ), and analyst estimates from the Institutional Brokers' Estimate System (IBES) in the calculation of several of our information asymmetry proxies. We gather data on special items (SPI), provisions for loan loss (PLL), and net charge offs (NCO) from the annual Compustat industrial data set for use in bath identification.[2] Please see the Appendix for the process we used to identify which Compustat firms are banks.

To identify when a bank takes a bath, we use SPI, NCO, and PLL, each divided by the prior year's total assets. As an increase in PLL adversely affects a bank's net income, we multiply it by -1 to give it the same sign as SPI and NCO. We classify any bank with the sum of PLL and NCO less than -1% as having a loan bath and any bank with SPI less than -1% as having a special items bath. As our goal is to examine the changes in opacity around baths, we include only baths that occur in isolation. Thus, we remove bath observations occurring within three years of another bath at the same firm from our sample.[3] Before confounding baths, we identify 2,919 (243) loan (special item)

[2] Because we measure information asymmetry using market and analyst data, we need to match bank accounting data to CRSP, IBES, and TAQ. We therefore collect bank accounting data from Compustat instead of directly from call reports.

[3] The screening process is applied separately to each bath sample. For instance, we remove special items baths if they occur within three years of another special items bath.

TABLE 1. Frequency of Bank Baths.

Year	Loan	Special	Year	Loan	Special
1974	2		2001	15	4
1975	12		2002	14	1
1976	3		2003	6	2
1977	1		2004	7	6
1978	1		2005	9	3
1979	1		2006	1	1
1980	2		2007	9	4
1981	1		2008	18	37
1982	7		2009	31	41
1983	7		2010	14	8
1984	1		2011	14	10
1985	7				
1986	2				
1987	7		Total	309	154
1989	1	1			
1990	6				
1991	11				
1992	3				
1993	5	4			
1994	19	4			
1995	15	3			
1996	16	1			
1997	16	2			
1998	11	8			
1999	3	6			
2000	11	8			

Note: The Appendix describes the sample of bank baths. We exclude baths that occur within three years of another bath (at the same firm). Reported in this table are the frequency of included baths and their mean size per year. PLL is provision for loan loss, NCO is net charge-offs, and SPI is special items. PLL is multiplied by -1 to represent a reduction in net income. Loan is the count of all firms with a sum(PLL,NCO) less than -1% of lagged total assets. Special is the count of all firms with a SPI less than -1% of lagged total assets.

baths between 1974 and 2011.[4] After excluding confounding baths, 309 (154) loan (special item) baths remain. Table 1 reports bath frequency by year. Although there is an uptick in baths around the financial crisis (55 and 72 total in 2008 and 2009, respectively), bank baths occur regularly throughout the 1990s and 2000s, providing a sample with substantial variation in macroeconomic conditions.

Given the differential opacity among bank assets identified by Haggard and Howe (2012), bank baths might have differential impacts on information asymmetry depending on the types of assets involved in the bath. Therefore, our analysis separately examines different types of baths. First, we divide the sample into loan baths (PLL, NCO) and special items baths (SPI). Then, we further divide special items baths into merger-related baths and other baths. As shown in Table 1, losses on loans drive a large majority

[4] We stop our bath identification in 2011 to allow three years of postbath data for our analyses. Though we have data back to 1962, we do not find any baths meeting our definition before 1974.

TABLE 2. Bath Summary Statistics.

	Loans			Special		
	PLL	NCO	SPI	PLL	NCO	SPI
Mean	–1.11%	–0.99%	–0.11%	–1.43%	–1.08%	–2.32%
1st percentile	–7.09%	–7.69%	–3.88%	–5.96%	–5.61%	–7.65%
10th percentile	–1.89%	–1.56%	–0.19%	–3.59%	–2.81%	–4.34%
25th percentile	–1.11%	–0.84%	0.00%	–1.94%	–1.58%	–2.56%
50th percentile	–0.79%	–0.57%	0.00%	–0.93%	–0.61%	–1.80%
75th percentile	–0.59%	–0.47%	0.00%	–0.31%	–0.25%	–1.29%
90th percentile	–0.53%	–0.33%	0.00%	0.00%	–0.04%	–1.08%
99th percentile	–0.07%	0.00%	0.67%	0.11%	0.00%	–1.01%

Note: Summary statistics are provided for both bath samples and their components. PLL = provision for loan loss; NCO = net charge-offs; SPI = special items. PLL is multiplied by −1 to represent a reduction in net income. Loans are baths with sum(PLL,NCO) less than −1% of lagged total assets Special are baths with SPI less than −1% of lagged total assets. PLL, NCO, and SPI are individual Compustat items divided by the prior year's total assets.

of baths (309). However, we find 154 baths with special items greater than 1% of total assets, which provides sufficiently large sample for separate analyses (and for subsequently breaking into subsamples).[5] Special items baths are concentrated in the latter half of our sample period, with half occurring during the financial crisis.[6] Therefore, we use a matched sample approach to control for the overall time-series changes in bank information environments, including the impact of the financial crisis.

Our use of two independently measured bath samples creates a concern of overlap, as loan and special items baths could occur simultaneously. Table 2 reports summary statistics for our three variables of interest (PLL, NCO, and SPI) scaled by the prior year's total assets for both bath samples. Our loan bath sample is largely free of substantial special items. The 10th percentile of special items is −0.19% of total assets. Only a small fraction of loan baths have special items sufficient to count as a bath on their own (the 1st percentile is −3.88%). There is more overlap in our special items bath sample. The 25th percentile PLL and NCO are −1.94% and −1.58%, respectively. However, given we find special items baths increase opacity and loan baths decrease opacity, this overlap understates the magnitude of the change in opacity for the special items bath sample.

We use propensity score matching to identify matching banks for the bathing banks in our sample. In each bath sample, we estimate propensity scores using a pooled logistic regression of an indicator variable for a bath regressed on the bank's prior-year log total assets, book-to-market ratio, net income, revenue, cumulative 12-month stock return, and an indicator variable equal to 1 if the firm had positive income and 0

[5] We are able to identify matches for 303 loan baths and 150 special items baths.

[6] Although we cannot be certain of the cause of the lack of special items baths before 1989, this is consistent with a sharp increase in the use of special items reporting in the 1990s discussed by Elliott and Hanna (1996), caused in part by the adoption of Statement of Financial Accounting Standards (SFAS) No. 121.

otherwise.[7] Our pool of firms for matching contains all the banks identified above, removing all banks with baths in the three years before or after the sample bank's bath.[8] We select the nonbath bank with the closest propensity score to the bath bank and the same month fiscal year-end as the bath bank's match, without replacement.

Table 3 reports the results of our matching procedure. Panel A reports the results of the pooled regression. Baths are inherently difficult to model and predict (Francis, Han, and Vincent 1996; Haggard, Howe, and Lynch 2015), as evidenced by the R^2 of 0.0206 (0.0017) for our special items (loan) baths. However, in Panel B we find considerable similarity between our bath and match samples. For our loan sample, book-to-market, revenue, positive income, and propensity score are all statistically indistinguishable. Our special items bath match is even better. All variables are statistically indistinguishable between the bath and match samples. Our final sample includes 303 (150) loan (special items) baths and 303 (150) matches.[9]

The opacity of a firm is difficult to measure, especially with any one proxy (Clarke and Shastri 2000). We therefore use nine proxies of information asymmetry in our analyses, drawing inferences from common changes across those proxies. Six of these are market-based measures created using data from the CRSP daily file, monthly for 1962 to 2011. *Turnover* is the monthly trading volume divided by shares outstanding. *Turnover* is inversely related to information asymmetry (Chae 2005). Daily spread (*DSpread*) is the monthly average of the daily high/closing ask price minus the low/closing bid price from CRSP. A greater value of this variable is related to greater information asymmetry due to the adverse selection component of the bid–ask spread (Lin, Sanger, and Booth 1995). *Roll* is the Roll (1984) covariance measure defined as $2*\sqrt{-\mathrm{Cov}\left(\triangle p_{i,t}, \triangle p_{i,t-1}\right)}$, where $\triangle p_t$ is the change in log price from end of day $t-1$ until the end of day t, set to 0 if the covariance is positive. *Roll* is positively related to information asymmetry. *Amihud* is the monthly average daily price impact measure described by Amihud (2002) and defined as $\left|Return_{i,t}\right|/DollarVolume_{i,t}$, where $DollarVolume_{i,t}$ is in millions of dollars. *Amihud* is positively related to information asymmetry. Realized volatility (*RStdev*) is the monthly sum of daily squared returns (French, Schwert, and Stambaugh 1987; Andersen et al. 2001). Return standard deviation (*Stdev*) is the monthly standard deviation of daily returns. Both of these return volatility measures are positively related to information asymmetry (Benston and Hagerman 1974; Chordia, Roll, and Subrahmanyam 2001).

We use a single analyst-based measure from the IBES data for 1976 to 2011. Analyst standard deviation (*AStdev*) is the standard deviation of all current annual

[7] This procedure is similar to that of Haggard, Howe, and Lynch (2015). However, they use annual cross-sectional regressions to estimate propensity scores. Given the smaller size of our sample, we use a pooled regression.

[8] Although we remove loan bath banks from the match pool for special items baths, we allow for the same bank match to match to both a special items bath and a loan bath. However, the two bath samples share only three matches.

[9] We lose six loan and four special items baths to either insufficient data for matching (missing Compustat items) or lack of a nonbath bank with same fiscal year-end with sufficient data for matching

TABLE 3. Matching Procedure.

Panel A. Propensity Score Estimation

	Loan		Special	
	Coefficient	p-value	Coefficient	p-value
Intercept	3.7462	< .0001	4.3146	< .0001
$Total\ Assets_{t-1}$	0.0243	.4701	–0.0956	.0400
$Book\text{-}to\text{-}Market_{t-1}$	4.3957	.5175	15.0218	.4752
$Net\ Income_{t-1}$	0.1340	.9547	–21.0936	.0304
$Revenue_{t-1}$	1.7722	.1947	14.0971	.0004
$Cumret_{t,t-1}$	0.7269	< .0001	4.0639	< .0001
$Positive_{t-1}$	–0.3138	.2145	0.4969	.1067
N (Baths = 1)	14,567		14,722	
N (Bath = 0)	303		150	
R^2	0.0017		0.0206	

Panel B. Bath and Match Sample Comparison

	Loan			Special		
	Bath	Match	t-stat	Bath	Match	t-stat
$Total\ Assets_{t-1}$	7.31	7.07	1.81	7.74	7.76	–0.07
$Book\text{-}to\text{-}Market_{t-1}$	0.16	0.25	–1.10	0.17	0.24	–0.72
$Net\ Income_{t-1}$	0.68%	0.84%	–2.20	0.40%	0.38%	0.11
$Revenue_{t-1}$	7.90%	7.96%	–0.25	7.20%	7.05%	0.51
$Cumret_{t,t-1}$	4.47%	8.51%	–1.24	–34.45%	–32.82%	–0.33
$Positive_{t-1}$	93.53%	96.70%	–1.82	79.22%	78.67%	0.12
Propensity Score	97.72%	97.78%	–1.04	93.06%	93.27%	–0.12

Note: We identify matched firms using propensity score matching. We run a pooled logistic regression on the entire CRSP/Compustat sample of bath firms as identified in the Appendix. We regress a bath indicator variable (equal to 1 for a firm in the year their bath occurred and 0 otherwise) on lagged firm characteristics: total assets, book-to-market, net income, revenue, cumulative 12-month stock returns, and an indicator variable equal to 1 if net income is positive and 0 otherwise. The propensity score used in matching is the model's estimated probability of a firm taking a bath. Baths are matched to the firm with the closed propensity score in the same month the bath occurred without resampling. If a firm had a bath but was excluded from the bath sample (i.e., confounding bath within three years, total assets below \$5 million), it is excluded from the pool of potential matches. Panel A reports the results from the logistic regression, run separately for both loan and special bath samples. Panel B reports the summary statistics of variables used to match, for both loan and special samples, and t-statistics for the difference between the bath and match samples.

earnings forecasts for the bank at the time earnings are announced and is calculated only for banks with estimates from more than one analyst. *AStdev* is positively related to information asymmetry (Kothari, Li, and Short 2009). Finally, we use two transaction-level measures calculated for 1993 to 2011 from TAQ data. Effective spread (*ESpread*) is the monthly average of the transaction-level calculation of $2*|\ln(Price)_{i,\tau} - \ln\left(Mid_{i,\tau}\right)|$, weighted by transaction dollar volume (Goyenko, Holden, and Trzcinka 2009). Quoted spread (*QSpread*) is the monthly average of the transaction-level calculation of $\frac{Ask_{i,\tau}-Bid_{i,\tau}}{Mid_{i,\tau}}$, weighted by transaction dollar volume.[10] Greater magnitudes of spreads indicate greater information asymmetry. We winsorize all measures at the 1st and 99th percentiles.

In addition to proxies for information asymmetry, we examine the responsiveness of bank abnormal stock returns to unexpected earnings pre- and postbath. Haggard, Howe, and Lynch (2015) provide evidence that the earnings announcements of more transparent firms are more credible and, ceteris paribus, create a stronger response to earnings announcements. Therefore, if a bath increases opacity, we expect earnings response coefficients (ERCs) to decrease postbath, as earnings surprises for more opaque banks are less credible. Conversely, if a bath decreases opacity, we expect ERCs to increase. We measure abnormal returns around announcements in two ways. First, we measure firm returns in excess of the CRSP value-weighted index return. Second, we measure abnormal returns in excess of the expected return estimated from the Fama–French (1993) three-factor model, with factor loadings estimated over the 180 calendar days before the earnings announcement. We estimate unexpected earnings as:

$$UE_{i,t} = \frac{A_{i,t} - F_{i,t}}{P_{i,t}}, \tag{1}$$

where $A_{i,t}$ is the actual quarterly reported earnings per share from Compustat, $F_{i,t}$ is the mean forecasted earnings per share as reported in the IBES database at the time of the earnings announcement, and $P_{i,t}$ is the stock's price at the close of trading at the end of the prior month from CRSP. We measure earnings responsiveness by regressing the cumulative abnormal return (CAR) for the three days surrounding the earnings announcement ($t-1$ through $t+1$) on unexpected earnings.[11]

We perform regressions that identify the differences in pre- and postbath changes between bath and nonbath banks. Our primary specification uses three indicator variables. *Bath* equals 1 for all bath banks and 0 for all matching (nonbath) banks. *Post* equals 1 for all observations that occur after the bath (or in the case of nonbath banks, after the matching bank's bath) and 0 otherwise. Finally, *Bath***Post* is the interaction between the *Bath* and *Post* indicator variables. Regressing bank characteristics on these three indicator variables provides a comprehensive picture of bath banks' characteristics and how they change around baths, both in absolute terms and relative to matched banks.

The coefficient on *Bath* illustrates differences, on average, between bath and nonbath banks. The coefficient on *Post* identifies the change in the variable of interest following the bath for all banks (both bath and nonbath). Most important to this study, the coefficient on the interaction of these two indicator variables (*Bath***Post*) shows the change in the variable of interest postbath for bath banks compared to nonbath banks. All

[10] In accordance with Chordia, Roll, and Subrahmanyam (2000), we filter transactions by discarding trades with a bid–ask spread greater than \$5, or an effective-to-quoted-spread ratio greater than 4, or a quoted proportional spread greater than 40%.

[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).

regressions use panel ordinary least squares (OLS) with standard errors clustered by time to estimate *t*-statistics.

IV. Results

Opacity

We begin our analysis by examining the change in nine information asymmetry proxies following a bath. Table 4 presents the univariate change in means of the information asymmetry proxies following loan and special items baths. The results provide both a cursory understanding of how baths affect opacity and a reference point for discussing the economic significance in our difference-in-difference analyses. Almost uniformly, opacity significantly decreases following loan baths. For instance, *Stdev* falls from 2.46% to 1.93%, a 21.54% reduction in volatility. *RStdev* is even more substantial, declining from 2.07% to 1.11% (a 46.38% decrease in volatility). *ESpread* decreases by 58 bps, a 26.98% reduction from its prebath mean of 2.15%, and *AStdev* decreases by 2.43%, a 28.32% decline from its 8.58% prebath level.

In contrast, opacity appears to increase following baths taken through special items, as six out of nine information asymmetry proxies increase significantly. *RStdev* increases from 3.15% to 4.53% (a 45.81% increase), *AStdev* increases by 3.26% (a 44.05% increase), and *ESpread* increases by 23.50% to 2.26%. Taken together with the loan bath changes in means, these results suggest that baths have a significant impact on the opacity of banks, and this impact is conditional on the source of the bath.

TABLE 4. Univariate Information Asymmetry Change.

		Loan Baths			Special Baths		
	Relation with IA	Prebath	Postbath	*t*-stat	Prebath	Postbath	*t*-stat
Turnover	−	0.0513	0.0461	–3.56	0.0836	0.0918	1.84
DSpread	+	0.0355	0.0265	–17.44	0.0400	0.0474	8.98
Roll	+	0.0104	0.0074	–16.74	0.0110	0.0116	1.42
Amihud	+	143.90	135.74	–1.00	207.40	157.70	–1.07
RStdev	+	0.0207	0.0111	–11.26	0.0315	0.0453	4.80
Stdev	+	0.0246	0.0193	–20.46	0.0300	0.0353	7.76
AStdev	+	0.0858	0.0615	–5.41	0.0740	0.1066	5.00
ESpread	+	0.0215	0.0157	–14.26	0.0183	0.0226	6.12
QSpread	+	0.0339	0.0249	–14.44	0.0306	0.0368	5.58

Note: Information asymmetry (IA) proxies are measured monthly for the 36 months before the bath (Prebath) and 36 months following the bath (Postbath). For all IA proxies, + (−) represents a positive (negative) relation with IA. The *t*-statistic reported is the Satterthwaite difference in means between the pre- and postbath months. *Turnover* is monthly volume divided by shares outstanding. *DSpread* is the difference between the high and low price during the day, divided by the closing price. *Roll* is the Roll (1984) liquidity measure. *Amihud* is the Amihud (2002) illiquidity measure. *RStdev* is realized volatility, defined as the monthly sum of squared daily returns. *Stdev* is the monthly standard deviation of daily returns. *AStdev* is the standard deviation of analyst estimates as reported in IBES. *ESpread* and *QSpread* are effective and quoted spreads, respectively, calculated from transaction-level TAQ data, and are the trade dollar-weighted average spreads over each month.

As it is possible other firm or market effects caused the changes in opacity found in Table 4, we employ a matched sample of similar banks that did not take a bath in our next analysis. Panel A of Table 5 reports the regression coefficients of information asymmetry proxies regressed on *Bath* and *Post* indicator variables, using the loan bath and match bank sample. We find two significant results in this analysis. First, opacity appears to decrease across all banks, both bath and match, in the three years following a bath. Examining the coefficient on *Post*, which is the marginal change in the dependent variable following a bath, *RStdev* decreases by 34 bps, *AStdev* by 41 bps, and *QSpread* by 44 bps. Intercepts show that *RStdev*, *AStdev*, and *QSpread* in our loan sample are, on average, 1.70%, 6.81%, and 3.29%, respectively, so these reductions are both statistically and economically significant. Six of our nine proxies are consistent with a decrease in postbath opacity.[12]

Our second significant result comes from our primary variable of interest, the interaction between the *Bath* and *Post* indicator variables (*Bath***Post*). This coefficient measures the change in opacity for bathing banks postbath, relative to the matched sample. In other words, this coefficient represents the change in bathing banks above the average change shown by all banks in the *Post* coefficient. Seven of nine proxies indicate a statistically significant decrease in opacity after banks take a bath. *RStdev* decreases by 62 bps, *AStdev* by 204 bps, and *ESpread* by 32 bps. The decreases in *RStdev*, *AStdev*, and *ESpread*, 29.95%, 23.78%, and 14.88% respectively, are economically significant relative to their prebath means in Table 4. We conclude that a loan bath coincides with a substantial improvement (greater transparency) in a bank's information environment.

Arguably more intriguing are the results from our special items bath sample, reported in Panel B of Table 5. We find two results that sharply contrast with the loan bath sample in Panel A. First, there is little change in average opacity across our entire special items subsample (both bath and match banks). Examining the coefficient on *Post*, turnover increases (suggesting a decrease in opacity). No other proxies show any significant change. Second, and more important, we find the *Bath***Post* coefficients on six of nine proxies suggest an increase in opacity in bathing banks postbath. *DSpread* and *ESpread* increase by 48 bps and 36 bps, respectively. *RStdev* and *Stdev* increase by 102 bps and 52 bps, respectively. Relative to the prebath means from Table 4, these are all economically large changes. For instance, *RStdev* increases by 32.38% and *ESpread* increases by 19.67%.

Information asymmetry exists when different market participants possess different information sets about firms. The public release of relevant information about a firm reduces the information imbalance. However, the public release of false or confusing information will, at best, have no impact on a firm's information environment and, at worse, degrade it. The results shown in Panels A and B of Table 5 tell quite different stories about the types of information released in loan baths and special items baths. Panel A suggests the information content of loan baths is relevant to banks and their equity holders. Although increasing provisions for loan loss and charging off loans

[12] To account for a potential secular decline in information asymmetry over our sample, we repeat the regressions using a time trend and year fixed effects. Our results, available upon request, are qualitatively similar.

TABLE 5. Information Asymmetry Analysis.

	Intercept	*Bath*	*Post*	*Bath***Post*	Adj. R^2	*N*
Panel A. Loan						
Turnover	0.0428	0.0088	–0.0040	–0.0007	0.0032	34,063
	(26.89)	(6.17)	(–2.16)	(–0.42)		
DSpread	0.0328	0.0026	–0.0052	–0.0037	0.0124	34,063
	(39.11)	(4.85)	(–7.59)	(–5.81)		
Roll	0.0098	0.0005	–0.00186	–0.0011	0.0105	31,123
	(25.86)	(3.51)	(–6.01)	(–5.09)		
Amihud	17.0174	124.6995	77.90507	–206.2120	–4.6E-05	30,552
	(1.72)	(0.97)	(0.83)	(–1.30)		
RStdev	0.0169	0.0036	–0.00335	–0.0062	0.0039	34,054
	(13.11)	(4.00)	(–3.81)	(–4.80)		
Stdev	0.0225	0.0021	–0.0018	–0.0035	0.0128	34,054
	(33.75)	(7.97)	(–3.69)	(–9.20)		
AStdev	0.0681	0.0175	–0.00405	–0.0204	0.0037	12,041
	(21.38)	(4.02)	(–1.15)	(–3.51)		
ESpread	0.0205	0.0008	–0.00269	–0.0032	0.0116	17,813
	(29.24)	(2.50)	(–4.31)	(–5.74)		
QSpread	0.0329	0.0009	–0.00438	–0.0050	0.0124	17,813
	(26.01)	(2.07)	(–3.83)	(–5.80)		
Panel B. Special						
Turnover	0.0793	0.0029	0.1187	–0.1105	0.0052	15,824
	(22.34)	(0.95)	(5.52)	(–5.13)		
DSpread	0.0399	0.0004	0.0026	0.0048	0.0069	15,824
	(15.49)	(0.91)	(1.35)	(4.29)		
Roll	0.0117	–0.0005	0.0009	–0.0003	0.0006	12,077
	(13.50)	(–1.79)	(1.29)	(–0.47)		
Amihud	2.6103	197.5553	0.3503	–194.7610	–2.6E–05	15,314
	(6.65)	(1.09)	(1.31)	(–1.07)		
RStdev	0.0359	–0.0037	0.0032	0.0102	0.0017	15,824
	(6.86)	(–1.984)	(0.77)	(3.99)		
Stdev	0.0295	0.0006	0.0001	0.0052	0.0068	15,824
	(15.23)	(1.65)	(0.04)	(6.29)		
AStdev	0.0981	–0.0221	0.0261	0.0079	0.0027	7,421
	(14.71)	(–3.84)	(1.60)	(0.54)		
ESpread	0.0230	–0.0039	0.0006	0.0036	0.0051	11,373
	(13.76)	(–6.54)	(0.38)	(4.42)		
QSpread	0.0371	–0.0055	0.0015	0.0049	0.0049	11,373
	(13.98)	(–7.92)	(0.61)	(4.50)		

Note: We regress proxies of information asymmetry on two indicator variables and their interaction. The regressions sample consists of monthly observations that occur within 36 months of a bath (for both bath and match firms, both pre- and postbath). *Bath* equals 1 if a firm is in our bath sample and 0 if in our matched sample. *Post* equals 1 for all firms (bath and match) for all months after the bath month and 0 if before. *Bath***Post* is the interaction of the two. *Turnover* is monthly volume divided by shares outstanding. *DSpread* is the difference between the high and low prices during the day, divided by the closing price. *Roll* is the Roll (1984) liquidity measure. *Amihud* is the Amihud (2002) illiquidity measure. *RStdev* is realized volatility, defined as the monthly sum of squared daily returns. *Stdev* is the monthly standard deviation of daily returns. *AStdev* is the standard deviation of analyst estimates as reported in IBES. *ESpread* and *QSpread* are effective and quoted spreads, respectively, calculated from transaction-level TAQ data, and are the trade dollar-weighted average spreads over each month. We report *t*-statistics in parentheses below coefficients based on standard errors clustered by time. Panel A reports results from regressions using just bath firms (and their matches) with provision for loan loss and net charge-offs in excess of 1% of total assets. Panel B reports results from regressions using just bath firms (and their matches) with special items in excess of 1% of total assets.

is not positive information about a bank, if those losses need to be taken to reflect the underlying economic reality of the bank, managers' public acknowledgment of such losses will improve the bank's information environment. This outcome occurs with the loan baths in our sample. Conversely, Panel B suggests the information content of special items baths is either nonexistent or misleading. Special items baths actually make banks more opaque.

To better understand the degraded information environment following special items baths, we break special items baths into two subsamples in Table 6. Special items are fairly generic and can include nearly any nonrecurring charge. Accordingly, we examine the 10-K filings for all special items bath banks in our sample and record the largest component of the special items amount in the year of their bath.[13] After observing the sources of these nonrecurring charges, we break them into two classifications: merger and nonmerger. Merger baths are those attributable either to the immediate costs incurred integrating two banks or to the costs of goodwill or other acquisition impairment following a merger or acquisition. These events account for 104 of our 150 special items baths. The remaining special item baths are varied, including everything from litigation provisions to regulatory fines. We group these baths together in the nonmerger classification.

Panel A of Table 6 reports the results of regressions using the merger subsample. Four of nine proxies show an increase in opacity for bathing banks postbath. Compared to the full special items subsample in Panel B of Table 5, and given that one of the proxies suggests a decrease in opacity, we find it difficult to draw conclusions about the merger subsample, though the results are consistent with merger baths increasing opacity. However, turning to the nonmerger subsample in Panel B, we find different results from the full special items baths subsample. First, examining *Post*, opacity increases for all firms (bath and match banks) postbath. Five of nine proxies increase significantly. Second, *Bath*Post* displays a decrease in opacity for bathing banks postbath. *DSpread* decreases by 69 bps, *RStdev* by 118 bps, and *AStdev* by 593 bps. These results indicate a more nuanced relation between special items baths and opacity. Although special items baths degrade a bank's information environment on average, their effect is highly dependent on the type of special item. Merger baths appear to increase opacity whereas nonmerger special item baths decrease opacity.

Time-Series Analysis

To this point, our analysis groups the three years following a bath together and measures the average postbath change in bathing banks' opacity. Our next analysis decomposes the postbath period into three separate years so we can assess how opacity changes over time following baths. There are two reasons for this approach. First, we want to measure how

[13] We are able to acquire 138 10-K reports from the SEC. Of those, 64 have only one item recorded under special items, 51 have two items, 15 have three items, 5 have four items, and 3 have five items. This situation creates some difficulty in classifying the special item bath. However, for baths with multiple special items, the largest item accounts for a substantial portion of total special items (84.54% and 88.68% mean and median, respectively), and only four banks have their largest item account for less than 60% of total special items (the lowest is 51.10%).

TABLE 6. Special Item Subsamples.

	Intercept	*Bath*	*Post*	*Bath***Post*	Adj. R^2	*N*
Panel A. Merger						
Turnover	0.0841	–0.0023	0.2132	–0.1934	0.0102	9,945
	(19.15)	(–0.69)	(6.18)	(–5.45)		
DSpread	0.0431	–0.0008	0.0043	0.0075	0.0144	9,945
	(12.94)	(–1.67)	(1.36)	(6.70)		
Roll	0.0129	–0.0012	0.0025	–0.0012	0.0035	7,119
	(11.00)	(–3.05)	(1.76)	(–1.87)		
Amihud	3.4160	295.7004	0.7663	–295.5800	–6.4E-05	9,601
	(5.73)	(1.08)	(1.71)	(–1.08)		
RStdev	0.0442	–0.0078	0.0066	0.0133	0.0030	9,945
	(6.09)	(–2.79)	(0.91)	(3.91)		
Stdev	0.0313	0.0003	0.0026	0.0056	0.0118	9,945
	(12.68)	(0.68)	(1.12)	(5.61)		
AStdev	0.1208	–0.0405	0.0317	0.0107	0.0034	4,515
	(14.06)	(–5.45)	(1.00)	(0.37)		
ESpread	0.0245	–0.0039	0.0049	0.0002	0.0104	7,215
	(11.31)	(–4.65)	(2.40)	(0.18)		
QSpread	0.0385	–0.0039	0.0089	–0.0007	0.0099	7,215
	(11.51)	(–4.30)	(2.62)	(–0.47)		
Panel B. Nonmerger						
Turnover	0.0725	0.0189	0.0018	–0.0127	0.0010	3,625
	(18.13)	(2.27)	(0.46)	(–1.44)		
DSpread	0.0294	0.0083	0.0077	–0.0069	0.0182	3,625
	(27.41)	(10.76)	(6.60)	(–6.01)		
Roll	0.0091	0.0019	0.0017	–0.0020	0.0025	3,159
	(21.85)	(3.38)	(1.96)	(–2.08)		
Amihud	1.2345	0.2673	0.9570	–1.2300	0.0073	3,552
	(6.97)	(0.59)	(2.54)	(–2.02)		
RStdev	0.0172	0.0107	0.0115	–0.0118	0.0059	3,625
	(10.33)	(5.57)	(4.06)	(–4.07)		
Stdev	0.0272	0.0017	–0.0034	0.0039	0.0076	3,625
	(23.51)	(2.60)	(–3.22)	(3.86)		
AStdev	0.0565	0.0157	0.0697	–0.05930	0.0221	1,880
	(14.75)	(2.33)	(5.11)	(–4.54)		
ESpread	0.0183	–0.0018	0.0005	0.0005	0.0010	2,965
	(22.27)	(–2.19)	(0.50)	(0.37)		
QSpread	0.0315	–0.0049	0.0006	0.0007	0.0043	2,965
	(26.18)	(–4.12)	(0.33)	(0.35)		

Note: We regress proxies of information asymmetry on two indicator variables and their interaction. The regressions sample consists of monthly observations that occur within 36 months of a bath (for both bath and match firms, both pre- and postbath). *Bath* equals 1 if a firm is in our bath sample and 0 if in our matched sample. *Post* equals 1 for all firms (bath and match) for all months after the bath month and 0 if before. *Bath***Post* is the interaction of the two. *Turnover* is monthly volume divided by shares outstanding. *DSpread* is the difference between the high and low prices during the day, divided by the closing price. *Roll* is the Roll (1984) liquidity measure. *Amihud* is the Amihud (2002) illiquidity measure. *RStdev* is realized volatility, defined as the monthly sum of squared daily returns. *Stdev* is the monthly standard deviation of daily returns. *AStdev* is the standard deviation of analyst estimates as reported in IBES. *ESpread* and *QSpread* are effective and quoted spreads, respectively, calculated from transaction-level TAQ data, and are the trade dollar-weighted average spreads over each month. We report *t*-statistics in parentheses below coefficients based on standard errors clustered by time. Panels A and B divide the special items sample from Panel B of Table 4 into two subsamples. Panel A uses just bath firms (and their matches) whose special items bath are predominantly through goodwill or merger expenses. Panel B uses just bath firms (and their matches) whose special items bath are predominantly through something other than goodwill or merger expenses.

permanent any change is. The change in opacity could be strong the year following the bath and weaken or reverse in successive years, which would suggest a transitory direct effect of the bath on banks' information environments. Alternatively, the effect could be constant or growing in the years following the bath, which would suggest a more permanent effect (as evidenced, for example, by a change in the quality of future earnings announcements).

Our second motivation for this time-series analysis is the seemingly inconsistent results we observe in the special items bath subsample regressions. Table 4 shows that opacity increases postbath for banks taking special items baths. However, when we break the special items baths into subsamples, merger baths show only a weak increase in opacity whereas nonmerger baths show a marginal decrease. Neither of these subsample results is consistent with the overall special items results, suggesting our specification is not capturing a facet of the postbath change in special items baths. Allowing for variation in coefficients over time allows us to explore this more complex relation.

Table 7 reports results from this modified specification, where we regress information asymmetry proxies on a bath indicator, three postbath year indicators, and the interaction of three time indicators (one each for postbath years 1, 2, and 3) with the bath indicator. Because we know loan and special items baths affect information environments differently, we report results in three panels for loans baths, merger baths, and other baths. Panel A reports results using the loan bath subsample and displays considerable variation in postbath interaction coefficients. Six of nine proxies display the largest decrease in opacity in year 3. For instance, *RStdev* decreases by 79 bps in year 1, 73 bps in year 2, and 95 bps in year 3. Relative to its prebath mean, this change represents a proportional decrease in volatility of 45.89% in year 3. Overall, the majority of the decrease in opacity occurs two to three years after the bath, suggesting the change is not a transitory result of the bath.

Panel B of Table 7 examines the merger special items subsample. Recall from Table 6 that there is little change in information asymmetry postbath for merger-related baths. In contrast to Table 6, Panel B of Table 7 shows that four of nine proxies suggest increased opacity for bathing banks in the first year following the bath. The increase, however, is transitory. *RStdev* and *Stdev* both show no statistical difference by year 3. *DSpread* remains higher for bath firms in year 3, but by an economically smaller 34 bps (relative to 1.27% in year 1). In year 3, two proxies (*Turnover* and *DSpread*) show increased opacity and two (*ESpread* and *QSpread*) show decreased opacity. We interpret this pattern in postbath coefficients as evidence that merger baths initially increase opacity, but the effect reverses over time.

We then examine nonmerger special item baths in Panel C of Table 7. Here, the time variation in coefficients is not as consistent. Five of nine proxies show a decrease in opacity in at least one year following the bath. However, six of nine proxies show increased opacity by year 3 following a bath. Although *ESpread* and *QSpread* decline by an insignificant 38 bps and 70 bps, respectively, in year 1, by year 3 they are significantly higher than matched banks by 72 bps and 78 bps. By year 3, *RStdev* and *Stdev* are 71 bps and 53 bps higher. These results indicate that although nonmerger baths reduce opacity initially, they result in high opacity in following years.

TABLE 7. Information Asymmetry over Time.

	Intercept	*Bath*	$Post_{t+1}$	$Post_{t+2}$	$Post_{t+3}$	$Bath^{*}Post_{t+1}$	$Bath^{*}Post_{t+2}$	$Bath^{*}Post_{t+3}$
Panel A. Loan								
Turnover	0.0436	0.0080	−0.0031	−0.0002	−0.0118	−0.0013	−0.0033	0.0022
	(25.88)	(6.03)	(−1.29)	(−0.06)	(−6.35)	(−0.79)	(−1.27)	(1.17)
DSpread	0.0327	0.0029	−0.0021	−0.0058	−0.0048	−0.0040	−0.0045	−0.0073
	(38.7)	(4.74)	(−3.09)	(−6.79)	(−5.45)	(−4.31)	(−6.23)	(−9.03)
Roll	0.0097	0.0007	−0.0005	−0.0020	−0.0022	−0.0020	−0.0013	−0.0013
	(26.13)	(3.89)	(−1.32)	(−5.22)	(−5.87)	(−5.44)	(−3.74)	(−4.23)
Amihud	6.4495	134.1550	−3.7563	−5.1268	−5.1559	−135.4500	−97.5000	−134.3900
	(1.51)	(1.06)	(−0.86)	(−1.2)	(−1.2)	(−1.07)	(−0.74)	(−1.06)
RStdev	0.0164	0.0048	−0.0004	−0.0029	−0.0029	−0.0079	−0.0073	−0.0095
	(13.06)	(5.10)	(−0.48)	(−2.41)	(−2.52)	(−4.88)	(−4.44)	(−6.89)
Stdev	0.0226	0.0022	−0.0007	−0.0028	−0.0026	−0.0035	−0.0031	−0.0045
	(33.62)	(8.17)	(−1.39)	(−4.11)	(−4.2)	(−6.05	(−6.32)	(−9.63)
AStdev	0.0607	0.0270	−0.0019	−0.0104	−0.0136	−0.0256	−0.0213	−0.0046
	(32.68)	(7.19)	(−0.66)	(−3.77)	(−4.6)	(−4.51)	(−4.12)	(−0.44)
ESpread	0.0216	0.0001	−0.0011	−0.0040	−0.0040	−0.0022	−0.0036	−0.0039
	(28.72)	(0.21)	(−1.56)	(−4.81)	(−5.48)	(−2.22)	(−4.81)	(−5.46)
QSpread	0.0343	−0.0001	−0.0006	−0.0062	−0.0070	−0.0033	−0.0066	−0.0062
	(25.52)	(−0.20)	(−0.53)	(−4.33)	(−5.62)	(−2.11)	(−5.25)	(−5.48)
Panel B. Merger								
Turnover	0.0977	−0.0134	0.04518	0.0738	0.0843	−0.0138	−0.0584	−0.0819
	(16.99)	(−4.39)	(6.48)	(6.14)	(4.45)	(−1.38)	(−4.55)	(−4.28)
DSpread	0.0417	0.0011	0.01065	−0.0031	−0.0113	0.0127	0.0087	0.0034
	(12.85)	(2.72)	(3.56)	(−0.92)	(−3.16)	(5.41)	(5.32)	(2.28)
Roll	0.0126	−0.0009	0.00601	−0.0024	−0.0051	0.0001	−0.0026	−0.0003
	(10.80)	(−2.87)	(3.66)	(−1.82)	(−4.03)	(0.09)	(−3.08)	(−0.4)
Amihud	244.2140	63.7322	−238.3200	−242.2200	−242.3700	−62.5060	−63.4860	−64.5550
	(1.02)	(0.17)	(−1.00)	(−1.02)	(−1.02)	(−0.17)	(−0.17)	(−0.17)
RStdev	0.0397	−0.0021	0.0151	−0.0107	−0.0222	0.0265	0.0218	0.0018
	(5.99)	(−1.14)	(2.11)	(−1.57)	(−3.15)	(3.87)	(2.28)	(0.69)
Stdev	0.0321	0.0002	0.0091	−0.0015	−0.0075	0.0080	0.0047	−0.0003
	(12.46)	(0.55)	(3.38)	(−0.55)	(−2.55)	(5.42)	(2.87)	(−0.30)
AStdev	0.1547	−0.0775	0.0389	−0.0077	−0.0294	0.0318	0.0393	0.0335
	(13.11)	(−12.16)	(2.58)	(−0.43)	(−1.37)	(1.58)	(1.72)	(1.24)
ESpread	0.0208	−0.0006	0.0090	0.0056	−0.0109	0.0044	−0.0079	−0.0039
	(12.34)	(−1.04)	(3.22)	(1.85)	(−5.68)	(1.98)	(−6.08)	(−3.67)
QSpread	0.0334	0.0011	0.0150	0.0138	−0.0182	0.0060	−0.0178	−0.0078
	(12.67)	(1.24)	(3.69)	(2.54)	(−6.16)	(1.48)	(−8.59)	(−4.97)

(Continued)

TABLE 7. Continued.

	Intercept	*Bath*	$Post_{t+1}$	$Post_{t+2}$	$Post_{t+3}$	$Bath^{*}Post_{t+1}$	$Bath^{*}Post_{t+2}$	$Bath^{*}Post_{t+3}$
Panel C. Nonmerger								
Turnover	0.0995	–0.0082	–0.0362	–0.0299	–0.0144	0.0364	0.0138	–0.0025
	(18.42)	(–0.85)	(–5.70)	(–4.47)	(–0.98)	(2.50)	(1.09)	(–0.13)
DSpread	0.0341	0.0040	0.0007	–0.0059	–0.0075	0.0026	0.0058	0.0054
	(23.47)	(5.89)	(0.25)	(–2.86)	(–5.48)	(1.41)	(2.94)	(3.18)
Roll	0.0096	0.0016	0.0018	–0.0036	–0.0036	–0.0025	0.0023	0.0043
	(16.91)	(2.97)	(1.41)	(–4.18)	(–4.95)	(–2.02)	(1.92)	(3.16)
Amihud	1.3368	0.1921	0.6728	–0.3466	–0.6718	–1.4807	0.2994	0.6573
	(10.87)	(0.44)	(1.28)	(–1.00)	(–1.81)	(–2.03)	(0.50)	(0.96)
RStdev	0.0248	0.0041	0.0038	–0.0077	–0.0129	–0.0006	0.0060	0.0071
	(10.37	(1.90)	(0.70)	(–2.25)	(–6.27)	(–0.13)	(1.40)	(2.18)
Stdev	0.0272	0.0020	0.0007	–0.0047	–0.0070	0.0011	0.0050	0.0053
	(23.2)	(3.04)	(0.31)	(–2.83)	(–6.24)	(0.67)	(2.80)	(3.48)
AStdev	0.1258	–0.0523	0.1261	0.0430	0.0134	–0.0904	–0.0328	–0.0381
	(15.85)	(–6.27)	(3.2)	(1.18)	(0.62)	(–2.23)	(–0.86)	(–1.7)
ESpread	0.0163	0.0003	0.0041	0.0036	–0.0055	–0.0038	–0.0027	0.0072
	(18.17)	(0.28)	(1.42)	(1.53)	(–5.19)	(–1.09)	(–0.90)	(3.23)
QSpread	0.0265	0.00031	0.0072	0.0080	–0.0051	–0.0070	–0.0074	0.0078
	(19.72)	(0.16)	(1.73)	(2.14)	(–2.50)	(–1.37)	(–1.66)	(2.10)

Note: We regress proxies of information asymmetry on indicator variables and their interaction. The regressions sample consists of monthly observations that occur within 36 months of a bath (for both bath and match firms, both pre- and postbath). *Bath* equals 1 if a firm is in our bath sample and 0 if in our matched sample. $Post_{t+1}$ equals 1 for all firms (bath and match) for months 1 through 12 after the bath month and 0 if not. $Post_{t+2}$ equals 1 for all firms (bath and match) for months 13 through 24 after the bath month and 0 if not. $Post_{t+3}$ equals 1 for all firms (bath and match) for months 25 through 36 after the bath month and 0 if not. *Bath*Post* is the interaction of the bath variables with the three postbath variables. *Turnover* is monthly volume divided by shares outstanding. *DSpread* is the difference between the high and low price during the day, divided by the closing price. *Roll* is the Roll (1984) liquidity measure. *Amihud* is the Amihud (2002) illiquidity measure. *RStdev* is realized volatility, defined as the monthly sum of squared daily returns. *Stdev* is the monthly standard deviation of daily returns. *AStdev* is the standard deviation of analyst estimates as reported in IBES. *ESpread* and *QSpread* are effective and quoted spreads, respectively, calculated from transaction-level TAQ data, and are the trade dollar-weighted average spreads over each month. We report *t*-statistics in parentheses below coefficients based on standard errors clustered by time. Panel A reports results from regressions using just bath firms (and their matches) with provision for loan loss and net charge-offs in excess of 1% of total assets. Panel B reports results from regressions using just bath firms (and their matches) with special items in excess of 1% of total assets that are predominantly due to goodwill impairment or merger expenses. Panel C reports results from regressions using just bath firms (and their matches) with special items in excess of 1% of total assets that are predominantly due to something other than goodwill impairment or merger expenses.

Earnings Response Coefficients

The changing magnitude of the effect of loan baths on opacity suggests the change in opacity is not an immediate response to the bath. If loan baths alleviate information asymmetry by better aligning bank financials with their underlying economic reality, loan baths could influence opacity indirectly through more accurate earnings disclosures. Our final analysis examines how ERCs change following baths.

We regress three-day CARs around quarterly earnings announcements on unexpected earnings, our bath and postbath indicator variables, and the interactions across all three variables. Panel A of Table 8 presents CARs calculated from daily returns in excess of the value-weighted market return. Examining the *UE*Post* interaction for loan baths, we find earnings responsiveness decreases (−0.4796) for all banks (bath and match samples) following baths, suggesting that a common factor across bath and match firms negatively influences the market's reactions to the unexpected portion of these firms' earnings.

Turning to our variable of interest, the interaction of *UE*Bath*Post*, we see bathing banks experience a relative increase in earnings responsiveness (0.5980), larger than the decrease seen across all sample banks. Netting the two coefficients, matched banks experience a decrease of 0.4796 whereas bathing banks experience an increase of 0.1186. Compared to the average earnings responsiveness of 0.5907, this 0.1186 increase is both statistically and economically significant. To account for possible differences in risk between our bath and match samples, in Panel B of Table 8 we show CARs using Fama–French (1993) three-factor adjusted daily returns and find similar results. Earnings responsiveness increases by 0.9872 for bath firms. Combining these results with our prior analyses, we attribute at least part of the decrease in opacity following loan baths to greater information content in earnings disclosures postbath.

For the sake of completeness, we test earnings responsiveness following special items baths. Given the time variation in the effect shown in Table 7, we do not expect to find a strong relation. As expected, we find no change in earnings responsiveness following special items baths.

V. Summary and Implications

We examine the impact of big baths at banks on the information environments of these firms. We find that, on average, baths at banks affect opacity, but in different ways depending on the type of bath. Baths associated with loans (provisions for loan losses and net charge-offs) decrease opacity. The reduction in opacity begins in the fiscal year following the bath and intensifies in the second and third fiscal years postbath. We also show that bank stock returns become more responsive to unexpected earnings after loan-related baths, suggesting that earnings convey more credible information after these baths.

Conversely, baths associated with special items result in an increase in opacity. Baths related to mergers and acquisitions drive an immediate increase in opacity, but the effect is transitory, existing only in the first fiscal year after the bath. The increase in

TABLE 8. Earnings Responsiveness.

	Loan		Special	
	Coef	*t*-stat	Coef	*t*-stat
Panel A. Excess Return				
UE	0.5907	2.22	–0.0237	–0.61
*UE** *Bath** *Post*	0.5980	2.45	–0.0139	–0.37
*UE** *Post*	–0.4796	–1.90	–0.0155	–0.41
*UE** *Bath*	–0.5507	–2.25	0.0500	1.29
*Bath** *Post*	0.0030	1.18	–0.0094	–2.10
Bath	–0.0016	–0.77	0.0026	0.84
Post	0.0015	0.68	0.0085	2.63
Controls	Yes		Yes	
N	3,944		2,931	
Adj. R^2	11.04%		3.31%	
Panel B. Alphas				
UE	0.9760	3.76	–0.0604	–0.90
*UE** *Bath** *Post*	0.9872	4.12	–0.0781	–1.21
*UE** *Post*	–0.8524	–3.46	0.0743	1.19
*UE** *Bath*	–0.9405	–3.92	0.0865	1.27
*Bath** *Post*	0.0013	0.59	–0.0068	–1.25
Bath	–0.0025	–1.32	–0.0019	–0.61
Post	0.0029	1.56	0.0042	1.15
Controls	Yes		Yes	
N	3,855		2,983	
Adj. R^2	14.56%		3.43%	

Note: We regress three-day cumulative abnormal returns ($\text{CAR}_{t-1,t+1}$) on unexpected earnings (*UE*), bath firms (*Bath*), postbath (*Post*), and the interaction among the three. Control variables include the signed square of *UE* to account for nonlinearity, variance of *UE* over the prior eight quarters, the beta of the stock for the CAR formation period (60 days), an indicator if earnings are negative, an indicator if the quarter is the last of the fiscal year, total market capitalization, and the market-to-book ratio. In Panel A, the dependent variable is the cumulative return in excess of the value-weighted market return. In Panel B, the dependent variable is the cumulative return in excess of three-factor expected returns (Fama and French 1993), with factor loadings estimated over the prior 180 calendar days.

opacity reverses over the second and third fiscal years following the bath. Special items baths not related to mergers and acquisitions see an initial reduction in opacity that reverses in the following two years, eventually resulting in increased opacity.

Our results have important implications for bank regulators, who use financial markets as one tool to monitor banks. Loan-related baths improve the information environments of bathing banks and stock returns are more responsive to unexpected earnings in the postbath period, both of which should increase the ease and effectiveness of monitoring such banks through financial markets.

Special items baths have the opposite effect on banks' information environments, which makes monitoring such banks through financial markets more difficult and less effective. Following such baths, regulators should consider increasing scrutiny of these bathing banks, perhaps through increased inspection frequency. The length of this scrutiny should be conditioned on the type of special items bath.

Our results are also relevant to investors and analysts. Short-term investors, sensitive to trading costs, can adjust their strategies based on changes in bid–ask spreads. Long-term investors, compensated for holding relatively illiquid securities, can make portfolio adjustments in response to changes in liquidity. Analysts, like regulators, should consider increasing their scrutiny of bathing banks whose transparency has decreased to improve the integrity of their analysis and recommendations.

Appendix: Identifying Banks

We begin by classifying all firms with Compustat Standard Industrial Classification (SIC) codes between 6000 and 6199 or 6710 and 6711 as potential banks. After examining these firms, we remove firms with Compustat SIC codes 6099, 6111, 6141, 6153, 6159, 6162, 6131, 6172, 6189, 6199, 6282, 6519, and 6798. Additionally, we remove firms that in an 10-K filing, self-identify an SIC code that is below 6000, above 7000, or in the prior list of SIC codes. Further examination of the sample and 10-K filings leads us to remove firms with the PERMNOs 63992, 75035, 10875, 87039, 84007, 77200, 90219, 11675, 40572, 70519, 89913, 85813, 79788, and 86161. We consider the remaining firms to be banks and use them to identify bank baths and create a matched sample for our analyses, as well as to visually inspect both the bath and match sample firms to verify they are banks.

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