OPEN ACCESS
Journal of Financial Management, Markets and Institutions
Vol. 10, No. 1 (2022) 2250002 (26 pages)

DOI: 10.1142/S2282717X22500025

THE IMPACT OF RESERVES PRACTICES ON BANK OPACITY

GIULIANO IANNOTTA[*,‡] and SIMON H. KWAN[†,§]

[*]*Universita Cattolica del Sacro Cuore, Italy*

[†]*Federal Reserve Bank of San Francisco, USA*

[‡]*giuliano.iannotta@unicatt.it*

[§]*simon.kwan@sf.frb.org*

Received 26 January 2022
Accepted 8 April 2022
Published 14 June 2022

This paper finds that banking firms' unexpected loan loss provisions had a significant effect of increasing bank opacity, both before and during the 2007–2009 financial crisis. Furthermore, during the financial crisis, the extent to which banks delayed loan loss recognition is found to have had a significant effect on bank opacity, confirming an important concern raised by the Financial Crisis Advisory Group. Overall, banks' practices in managing reserves seem to have a material impact on their opacity.

Keywords: Bank opacity; loan loss reserve; delays in loss recognition.

JEL Classifications: G21, G30, G34

1. Introduction and Motivation

During the 2007–2009 financial crisis, bank opacity appeared to play a central role that led to the seizing up of the interbank funding market, when even sophisticated financial institutions were reluctant to lend to each other (Kwan 2010). Impediments in the interbank market reflected uncertainty about counterparty solvency, or bank opacity, according to both Heider *et al.* (2009) and Pritsker (2010). The evidence in Flannery *et al.* (2013) further revealed that measures of bank opacity skyrocketed during the crisis. To the extent that bank opacity could be destabilizing when the financial system is under stress, understanding the source of bank opacity is important for formulating policy to enhance financial stability.

In the banking literature, researchers have made progress to address the fundamental question of whether banks are opaque.[a] However, pinning down the economic factors that contributed to bank opacity is challenging. Further complicating this inquiry is that bank opacity seems to be time-varying, as reported in Flannery *et al.* (2013), suggesting that understanding the dynamics of the relationship is equally important.

In this paper, we examine a specific area of concern that was raised by the body that establishes financial accounting standards in the United States — the Financial Accounting Standards Board (FASB) — regarding the accuracy of financial statements in reporting credit impairments of loans on bank balance sheets, and hence banks' true economic capital. In late 2012, the FASB proposed updating the accounting standards governing the reporting of credit losses in financial firms, and acknowledged that "the overstatement of assets caused by a delayed recognition of credit losses associated with loans was identified as a weakness in the application of existing accounting standards" (FASB 2012).[b] This motivates our study of the relation between banks' loan loss reserves practices and their opacity.

Even before the FASB acknowledged the weakness in the current reporting standards for credit impairments, researchers found evidence of earnings management in banking for quite some time, including for example Beatty *et al.* (1995), Beaver and Engel (1996), Ahmed *et al.* (1999), Beatty *et al.* (2002) and Cornett *et al.* (2009). In this literature, how banks provision for loan and lease losses has been identified as an important area bank management uses to manipulate reported earnings.

Of course, earnings management is also practiced by nonbanking firms. The agency problem between firms' dispersed owner-investors and the managers hired to run them could give rise to earnings management [see, for example, Healy (1985), Bergstresser *et al.* (2006), Cornett *et al.* (2008), and the review article by Healy and Wahlen (1999)]. Despite the sharp rise in both stock-based and options-based executive compensations over the past two decades, both Hall and Liebman (1998) and Bergstresser and Philippon (2006) found evidence that more "incentivized" CEOs — those whose overall compensation is more sensitive to company share prices — lead companies with higher levels of earnings management. Note that this literature tends to emphasize the question of why firms engage in earnings management; in this study, we instead emphasize the effects of such practices on bank transparency, in light of the implications for financial fragility.

Moreover, issues about reserve practices by banks are further complicated by banking regulation, which has the objective to promulgate bank safety and soundness.[c] As such, banking regulators may have a bias in favor of higher loan loss

[a] See Morgan (2002), Flannery *et al.* (2004), Iannotta (2006), Hirtle (2006), and Jones *et al.* (2012).

[b] This was identified by the Financial Crisis Advisory Group, which was created in October 2008 by the FASB and the International Accounting Standards Board (IASB) to deal with the reporting issues arising from the global financial crisis.

[c] Section 2 discusses current accounting standards and regulatory policy in banking related to credit impairments.

provisions to increase a banking firm's capacity to absorb losses through accumulating a higher reserve for future credit impairments. This additional layer of regulatory objective could either enhance or undermine the transparency of banking firms' financial statements. Both the subjectivity of banking supervisors and the judgments made by bank management in using reserves to guard against credit impairments could lead to cross-sectional variations across banks, and hence to different levels of accuracy in their financial statements. In this paper, we empirically examine how this management of reserves affects a bank's opacity.

To measure bank opacity, we follow Flannery *et al.* (2004, 2013) and construct five empirical measures using equity and microstructure data. Using high-frequency equity market data to construct the opacity measures allows us to exploit the time-varying properties of the data, especially during the financial crisis.

Banks' loan loss reserves practices can be motivated by risk preferences and agency issues, subject to accounting rules and supervisory oversight. To measure banks' reserves practices, we follow two strands of accounting literature. First, similar to Beatty *et al.* (2002), we model banking firms' provision for loan and lease losses using their observable characteristics; any unexplained provisions for losses are used as our measure of discretionary decisions. Second, similar to Beatty and Liao (2011), we measure whether a banking firm delays its loan loss recognition by how much it allows in current provisions for future nonperforming loans. This presumably reflects the loan officer's inside information about the changing prospects of the borrower. We are agnostic about which measure of discretionary provisioning should be preferred, and recognize the challenges of modeling agents' behavior in a parsimonious way.

Our findings indicate that bank practices regarding reserves have a significant impact on their stocks' microstructure trading properties, including bid-ask spreads, price impact, shares turnover, and return volatility. The results provide a link between how reserves are managed and bank opacity. However, our findings are sensitive to the way we model the reserve practices, as well as the sampling period.

The rest of the paper is organized as follows. In Sec. 2, we describe the supervisory guidance on loan loss provisioning in U.S. banking. Section 3 reviews the literature on discretionary provisioning and bank opacity. Section 4 presents our empirical framework. The empirical results are provided in Sec. 5. Section 6 concludes.

2. Accounting Standards and Regulatory Guidance on Credit Impairments

The reporting of credit impairments is arguably one of the most opaque areas on bank balance sheets. Although the FASB established accounting standards for how to report contingencies and loan impairments, bank management has some discretion on both when to recognize credit impairments and how much to hold in reserve against expected future loan losses. This is further complicated by banking supervision and regulation, whose mandate is a safe and sound banking system. As such, banking supervisors may have a bias in preferring banks to set aside more reserves against future loan losses. Moreover, the prudential supervision of a bank's allowance for loan and lease losses (ALLL) is inherently difficult to standardize due to many unobservable parameters, including a bank's private information about its borrowers' creditworthiness. Therefore, banking supervisors have to exercise a great deal of judgment in examining a bank's ALLL. At the end, it seems reasonable to characterize the supervisory process of a bank's ALLL as an exercise of supervisory judgment over the bank management's judgment about the quality of the bank's loan portfolio, a guesstimate of a guesstimate.

To report loan impairments, a bank sets aside an ALLL on the bank's balance sheet; the ALLL is a contra-asset that reduces the total (gross) amount of the bank's outstanding loan portfolio. The purpose of the ALLL is to reflect estimated credit losses within a bank's portfolio of loans and leases. Credit loss estimates are for the current amount of outstanding loans that the bank probably will not be able to collect given the facts and circumstances since the balance sheet date. In other words, estimated credit losses represent net charge-offs that are likely to be realized for a loan or group of loans as of the evaluation or balance sheet date.

The principal sources of guidance on accounting for impairment in a loan portfolio under generally accepted accounting principles (GAAP) are the Statement of Financial Accounting Standards No. 5, "Accounting for Contingencies" (FAS 5), and the Statement of Financial Accounting Standards No. 114, "Accounting for Creditors for Impairment of a Loan" (FAS 114).

FAS 5 requires the accrual of a loss contingency when information available before the financial statements are issued indicates it is probable that an asset has been impaired and the amount of loss can be reasonably estimated. These conditions may be considered in relation to individual loans or groups of similar types of loans. Under FAS 114, an individual loan is impaired when, based on current information and events, it is probable that a creditor will be unable to collect all amounts due according to the contractual terms of the loan agreement. Implicit in these conditions is that one or more future events is likely to occur confirming the loss. Thus, under GAAP, the purpose of the ALLL is not to absorb all of the risk in the loan portfolio, but to cover probable credit losses that have already been incurred as of the evaluation date due to observable triggers (for example, delinquency). Since the ALLL cannot be used to absorb future loss that has not been incurred as of the evaluation date when there has not been a triggering event, it is reasonable to expect that the ALLL would not be enough to cover lifetime expected loss in the loan portfolio.

Regarding regulatory policy, in 1999, the banking agencies in charge of banking supervision (including the Federal Reserve, the Office of the Comptroller of the Currency, and the Federal Deposit Insurance Corporation) and the Securities Exchange Commission (SEC), which recognizes the FASB, issued a joint interagency letter to U.S. financial institutions on the ALLL policy. This letter stated that the agencies and the SEC agreed on the following important aspects of loan loss allowance practices:

- Arriving at an appropriate allowance involves a high degree of management judgment and results in a range of estimated losses;
- Prudent, conservative, but not excessive, loan loss allowances that fall within an acceptable range of estimated losses are appropriate. In accordance with GAAP, an institution should record its best estimate within the range of credit losses, including when management's best estimate is at the high end of the range;
- Determining the allowance for loan losses is inevitably imprecise, and an appropriate allowance falls within a range of estimated losses;
- An "unallocated" loan loss allowance is appropriate when it reflects an estimate of probable losses, determined in accordance with GAAP, and is properly supported;
- Allowance estimates should be based on a comprehensive, well-documented, and consistently applied analysis of the loan portfolio; and
- The loan loss allowance should take into consideration all available information existing as of the financial statement date, including environmental factors such as industry, geographical, economic, and political factors.

Although the ALLL policy statement has been updated a few times since 1999, the above policy aspects remain in force today.

Under the current accounting standards for reporting credit impairments and the supervisory guidance, it is reasonable to conclude that the ALLL on bank balance sheets is an imprecise estimate that is likely to underestimate the lifetime expected loss of the loan portfolio due to the "incurred loss" framework underlying FAS5 and FAS114. More importantly, bank management has discretion in recognizing (or not recognizing) certain triggering events that may not be independently verifiable. Moreover, in reserving against incurred losses, bank management also has discretion in choosing the data and methodology for estimating that loss. Finally, bank managers who have every intention to follow accounting rules and supervisory guidance may have differences in both their individual judgment and level of conservatism. Hence, it seems reasonable to argue that a bank's choices in managing reserves against future loan losses constitute an important source of its opacity.

While we argue that how reserves are managed is expected to affect bank opacity, we are agnostic about banks' motivation in provisioning for loan losses in a particular way at a particular time. Our view is that this is a behavioral issue that could be driven by different objectives, including income smoothing, meeting regulatory capital requirements, and masking the true portfolio quality, which are beyond the scope of our analysis. The implication is that the model for how banks manage reserves needs to be flexible. To that end, we model bank discretion in loan loss provisioning in two different ways to provide some richness to the analysis.

3. Empirical Framework and Data

In this section, we lay out the empirical framework to examine the relation between reserve practices and bank opacity. We organize the discussion by first delving into the key empirical measures, followed by the regression model, data, and descriptive statistics.

3.1. *Discretionary provisioning*

One way to model banks account for reserves is to rely on certain observable bank characteristics that have plausible explanatory power for loan loss provisions, and then assume that any unexplained loan loss provision captures bank management discretion. We follow Beatty *et al.* (2002) and Cornett *et al.* (2009) by specifying a parsimonious pooled time-series cross-section regression model to explain the observed provision for loan and lease losses by bank i at quarter t using a set of bank characteristics, bank fixed effects (to absorb bank-specific factors), and time effects (to absorb economy-wide factors). The residual term in this regression, or the unexplained portion of the provision for loan and lease loss, is assumed to proxy for discretionary provisioning. Regarding bank characteristics, the amount of provisioning is assumed to be directly related to the quantity of newly delinquent loans in the bank's portfolio, as well as the amount of reserves the bank has already set aside to absorb future loan losses. Furthermore, we also control for bank size and loan composition. Hence,

$$\begin{aligned}\mathrm{LLP}_{i,t} = {}& \beta_0 + \beta_1 \ln(A_{i,t}) + \beta_2 \Delta\mathrm{NPL}_{i,t} + \beta_3 \mathrm{ALLL}_{i,t-1} + \beta_4 \mathrm{Loan}R_{i,t} \\ & + \beta_5 \mathrm{Loan}C_{i,t} + \beta_6 \mathrm{Loan}D_{i,t} + \beta_7 \mathrm{Loan}A_{i,t} + \beta_8 \mathrm{Loan}I_{i,t} \\ & + \beta_9 \mathrm{Loan}F_{i,t} + \mathrm{BANK} + \mathrm{TIME} + \varepsilon_{i,t}, \end{aligned} \tag{3.1}$$

where $\mathrm{LLP}_{i,t}$ is the ratio of loan loss provisions to total loans for the bank i at quarter t; $\ln(A_{i,t})$ is the natural log of the bank's total assets; $\Delta\mathrm{NPL}_{i,t}$ is the change in nonperforming loans from quarter $t-1$ to quarter t, deflated by total loans; $\mathrm{ALLL}_{i,t-1}$ is the ratio of allowance for loan and lease loss to total loans at quarter $t-1$; Loan$R$, Loan$C$, Loan$D$, Loan$A$, Loan$I$, and Loan$F$ are the loan shares in real estate lending, commercial and industrial lending, lending to depository institutions, agriculture lending, consumer lending, and lending to foreign governments, respectively; BANK is the bank fixed effect; and TIME is the quarter dummy. The absolute value of the residual term $\varepsilon_{i,t}$ from Eq. (3.1), renormalized by total assets, is our measure of discretionary loan loss provisioning:[d]

$$\mathrm{Abs}(\mathrm{DLLP}_{i,t}) = |\varepsilon_{i,t}| \cdot \frac{L_{i,t}}{A_{i,t}}. \tag{3.2}$$

3.2. *Delays in loss recognition*

Another way to model reserve practices is to construct a measure of the extent to which a bank delays loan loss recognition. The economic rationale is that at time t,

[d] Using the residual term $\varepsilon_{i,t}$ from Eq. (3.1), rather than its absolute value, to measure discretionary provisioning provides qualitatively similar results.

bank management may have private information about future loan performance, but it has discretion whether to recognize the expected future losses at time t or delay the loss recognition. Under timely recognition of future expected losses, the change in nonperforming loans in future quarters could have explanatory power for the current provision for loan loss. Following Beatty and Liao (2011) and Bushman and Williams (2012), we measure how quickly banks recognize future nonperforming loans today by comparing the goodness-of-fit (R^2) of two regressions of loan loss provisions where one regression includes current and future changes in nonperforming loans as additional explanatory variables. Specifically, for each bank quarter, the following two equations are fitted using quarterly data from a three-year rolling window:

$$\begin{aligned}\mathrm{LLP}_t = \beta_0 + \beta_1 \Delta\mathrm{NPL}_{t-1} + \beta_2 \Delta\mathrm{NPL}_{t-2} + \beta_3 \mathrm{Capital}_{t-1} + \beta_4 \mathrm{EBLLP}_t \\ + \beta_5 \ln(A_{t-1}) + \varepsilon_t, \end{aligned} \tag{3.3}$$

$$\begin{aligned}\mathrm{LLP}_t = \beta_0 + \beta_1 \Delta\mathrm{NPL}_{t-1} + \beta_2 \Delta\mathrm{NPL}_{t-2} + \beta_3 \Delta\mathrm{NPL}_t + \beta_4 \Delta\mathrm{NPL}_{t+1} + \beta_5 \mathrm{Capital}_{t-1} \\ + \beta_6 \mathrm{EBLLP}_t + \beta_7 \ln(A_{t-1}) + \varepsilon_t, \end{aligned} \tag{3.4}$$

where $\Delta\mathrm{NPL}_t$ is the change in nonperforming loans from quarter $t-1$ to quarter t, divided by total loans in quarter $t-1$. Unlike Eq. (3.1) where we model the cross-section and time-series variations of loan loss provision, Eqs. (3.3) and (3.4) are time-series regressions per bank over a three-year period. In the rolling regressions, we also control for both capital adequacy and gross earnings: *Capital* is measured as the Tier 1 regulatory capital ratio, and EBLLP is earnings before loan loss provisions and taxes, divided by lagged total loans.

For each sample bank, the incremental R^2 from fitting Eq. (3.4) relative to Eq. (3.3) indicates the extent to which current loan loss provisioning captures future changes in nonperforming loans. Specifically, at each quarter, we rank the sample banks by the change in the adjusted R^2 between Eqs. (3.3) and (3.4). For each bank-quarter, the variable LowDELR (which stands for low delayer) equals one if the sample bank is above the sample median of the change in R^2 at that quarter, and zero otherwise.

3.3. *Bank opacity*

Following Flannery *et al.* (2004, 2013), we construct five empirical measures of bank opaqueness based on banking firms' stock trading properties, including bid–ask spread (ESPREAD), adverse selection component of spread (AS), price impact (IMPACT), trading activity (TOVER), and stock return volatility (VOL). For each sample banking firm, we compute the five market microstructure variables using all available trades from a given day, and the daily values are averaged to provide quarterly observations.

The motivation of using market microstructure properties to measure opacity stems from Kyle (1985), who argued that more opaque stocks expose market makers to higher risk from being exploited by an informed trader. The likelihood of trading with an informed trader increases when market makers post too high the bid price or too low the ask price. More opaque stocks should then be associated with a greater adverse selection cost of trading.[e]

The adverse selection component of a stock's bid-ask spread cannot be observed and must be estimated by fitting transactions and quote data to a specific model. The methodology in George *et al.* (1991) is employed to compute the adverse selection component of the bid-ask spread as a proportion of the share price.

For robustness, we also include a stock's effective spread to proxy for the adverse selection.[f]

$$\text{ESPREAD} = \sum_{n} \frac{2 * ((Q_\tau - P_\tau) * I + (P_\tau - Q_\tau) * (1 - I))/Q_\tau}{n},$$

where P_τ is the trade price,
I is an indicator equal to unity for a bid-initiated trade or zero for an ask-initiated trade (based on Lee and Ready 1991),
Q_τ is the average of the bid and ask prices associated with the τth trade and
n is the number of trades within a day.

The price impact reflects the permanent (as opposed to the transient) component of the price change induced by a trade. According to Kyle (1985), trades by informed traders will move a stock price towards its (unobserved) fundamental value, while uninformed ("noise") trades are not expected to affect prices permanently. In other words, more private information (opacity) raises a stock's price impact. Following Amihud (2002), IMPACT, the permanent effect of a trade on share price, is measured by

$$\hat{\lambda} = \left(\frac{1}{n} \sum_{n} \frac{|\Delta P_t|}{\text{Size}_t} \right) * 10^6,$$

where $\Delta P_t = \text{LN}(Q_{t+5} - Q_t)$.
Q_t and Q_{t+5} are the matched mid-quotes for the trade closest to five seconds before and five minutes after the trade.
Size_t is the size of the trade or number of shares traded.
n is the number of trades within a day.
The variable is scaled by 10^6 to avoid reporting a large number of leading zeros in its summary statistics.

[e]Brennan & Subrahmanyam (1995) found that stocks' adverse selection component of bid–ask spread decreases with the number of analyst following the stock. Krinsky & Lee (1996) reported an increase in stocks' adverse selection component of spread two days before the earnings announcement is released to the public.

[f]Besides compensating for adverse selection, the bid–ask spread covers the market maker's operating costs. While free from estimation errors, using the effective spread to measure opacity assumes that market makers have about the same operating costs for all stocks.

IMPACT thus reflects the ratio of informed to uninformed traders in the market. A higher value of IMPACT implies greater information asymmetry, or opaqueness, in the associated stock.

Turning to the relation between trading activities and opacity, it is possible that opacity could reduce a stock's liquidity when uninformed traders rationally exit the market to avoid being exploited by informed traders (Gorton and Pennacchi 1990). In the limit, opacity could lead to market failure, as in Akerlof (1970). However, opacity also could raise trading activities, to the extent that traders who disagree about the true value of the stock may trade with each other more frequently (Harris and Raviv 1993); if everyone agreed on the stock price, there would be no trading. Bessembinder *et al.* (1996) found that trading volume is related to firm-specific information flows, thus suggesting a positive relation between informed trading and volume. We measure trading activity by turnover, TOVER, which is defined as the number of shares traded divided by the average number of shares outstanding during the quarter.

Our final measure of bank opacity is its stock return volatility. Volatility can arise from noise, or uninformed trading, referred to in the literature as transitory volatility, or it can be due to the release of new information, referred as fundamental volatility. Transitory volatility tends to be low in very liquid markets. Fundamental volatility, however, could be a result of informed trading. We measure the daily return volatility in percent as follows:

$$\mathrm{VOL} = (\mathrm{STD}) \times \sqrt{n} \times 100,$$

where STD is the standard deviation of the continuously compounded returns based on the quote midpoint associated with each trade within a day; and n is the number of trades within a day.

3.4. *The regression model*

In the first set of analysis, we examine the effects of unexplained provision on bank opacity by specifying the following regression model:

$$\begin{aligned}\mathrm{Opacity}_{i,t} = {} & \alpha_{i,t} + \beta_1 \mathrm{Abs}(\mathrm{DLLP}_{i,t}) + \beta_2 \mathrm{Abs}(\mathrm{DLLP}_{i,t-1}) + \beta_3 \mathrm{MVLEV}_{i,t} \\ & + \beta_4 \mathrm{PINV}_{i,t-1} + \beta_5 \mathrm{Ln}(\mathrm{MVEQ}_{i,t-1}) + \sum_q \chi_q D_q + \lambda_{i,t},\end{aligned} \tag{3.5}$$

where $\mathrm{Opacity}_{i,t}$ is AS, ESPREAD, IMPACT, TOVER, or VOL as defined above. Following the market microstructure literature and Flannery *et al.* (2004, 2013), we include the following control variables: $\mathrm{MVLEV}_{i,t}$, the sum of book value liabilities and market value equity at the end of quarter $t-1$, divided by the market value of equity at end of quarter $t-1$, controls the effect of leverage on microstructure properties. $\mathrm{PINV}_{i,t-1}$, the inverse of the average stock price during the quarter ending at $t-1$ controls the effect of the level of stock price on trading properties

(Madhavan 2000). Ln($\mathrm{MEVQ}_{i,t-1}$), the natural log of lagged market value of common equity at the end of quarter $t-1$ controls for the size effect.[g] D_q is the time effect (quarter) dummy.

In the second set of analysis, we examine how delays in recognizing loss affects bank opacity by replacing the first two right-hand-side variables in Eq. (3.5) with LowDELR.

$$\begin{aligned}\mathrm{Opacity}_{i,t} = \alpha_{i,t} + \beta_1 \mathrm{LowDELR}_{i,t} + \beta_2 \mathrm{MVLEV}_{i,t} + \beta_3 \mathrm{PINV}_{i,t-1} \\ + \beta_4 \mathrm{Ln}(\mathrm{MVEQ}_{i,t-1}) + \sum_q \chi_q D_q + \lambda_{i,t}.\end{aligned} \tag{3.6}$$

3.5. *Data and descriptive statistics*

We identified a sample of publicly traded bank holding companies (BHCs) that file the Federal Reserve's Consolidated Financial Statements for Bank Holding Companies (FR Y-9C), where we obtain the data for the financial variables in Eqs. (3.2) and (3.4). We then examined TAQ transactions data for these BHCs, and eliminated firms with insufficient trades to permit reliable estimates of the firm's market microstructure properties. In particular, we omitted any BHC-quarter for which the stock had fewer than 100 trades, the average quoted spread exceeded 10% of the share's price, or the average share price was less than \$2. We also omit any firm-quarter in which the stock had a split or paid a stock dividend greater than 10%, because research suggests significant microstructure changes following a split (Desai *et al.* 1998).

The final sample consists of 15,142 firm-quarters for NASD BHCs and 4,420 firm-quarters for NYSE BHCs. For each sample BHC, we compute each of the five market microstructure variables using all the trades from a given day, and the daily values are averaged to provide quarterly observations. In Table A.1, panel A provides descriptive statistics for the variables to fit the discretionary provisioning regression in Eq. (3.1) and the delays in loss recognition regressions in Eqs. (3.3) and (3.4); panel B provides descriptive statistics for the five measures of bank opacity, as well as the control variables in Eq. (3.5).

Since the findings in both Flannery *et al.* (2013) and FASB (2012) suggest that the financial crisis of 2007–2009 was unique in bank opacity and financial (mis-) reporting, our analysis is conducted for the full sampling period of 1994/1999 to 2009 and two subperiods separating the pre-crisis period and the financial crisis period: 1994:Q1/1999:Q1 to 2007:Q2, and, 2007:Q3 to 2009:Q4.[h]

[g] Since our opacity measures are derived from stock trading properties, the market capitalization is a more natural measure of bank size.

[h] The analysis of discretionary provisioning and bank opacity uses data from 1994 to 2009. The analysis of delays in loss recognition and opacity uses data from 1999 to 2009 since tier-1 capital ratio started in 1999.

4. Results

4.1. *Unexplained loan loss provision and bank opacity*

The regression results of fitting Eq. (3.1) for the full sampling period and the two subperiods of before and during the financial crisis are provided in Table A.2. To save space, the coefficients of bank fixed effects and time effects are not reported. The majority of the firm fixed-effect coefficients are statistically significant, likely due to firm-specific factors in determining loan loss provisioning including local economic conditions and bank-specific risk-taking and reserves behavior. Many time-effect dummies also are significant, likely reflecting the macroeconomic effects on loan portfolio performance. In addition to firm fixed effects and time-effects, a number of explanatory variables in Table A.2 are statistically significant in explaining loan loss provisioning. The lagged ALLL is significantly positive for the full sampling period and the two subperiods. The positive coefficient of lagged ALLL suggests that, after controlling for firm fixed effects, banking firms with larger reserves for loan and lease loss also tend to provision more. First, this is consistent with the mechanical relationship that higher quarterly provisioning results in a bigger cumulative reserve for loan loss. Second, this may reflect the risk preference of the banking firm in both its reserves practices and loan portfolio quality.

Change in nonperforming loans, Δ NPL, is also significant and positive across the three sampling periods, suggesting that banking firms tend to provision more amid rising nonperforming loans. The coefficient estimate of Δ NPL is twice as large during the financial crisis than before the crisis.

Loan portfolio compositions are found to be mostly insignificant except in a few cases where the coefficients are negative. All else equal, larger firms tend to provision more before the financial crisis, but the effect of bank size reverses sign during the crisis.

Based on the adjusted R^2 in Table A.2, the data fit the loan loss provisioning model much better during the financial crisis (45%) than before the financial crisis (21%), most likely due to the time dummies during the crisis. This implies the unexplained loan loss provision was bigger before the financial crisis than during the financial crisis, which by construction means more discretionary provisioning before the crisis than during the crisis.

The effects of unexplained loan loss provision on bank opacity are presented in Table A.3, which reports the regression results of fitting Eq. (3.5) separately for the five measures of bank opacity for the full sample period. Because market microstructure is systematically related to the stock's trading platform, the analysis is conducted separately for bank stocks that are traded at the NYSE versus the NASD. Our proxies for discretionary provisioning, Abs(DLLP) and lagged Abs(DLLP), have significantly positive effects on bank stock turnover, TOVER, and volatility of returns, VOL. Lagged Abs(DLLP) is significantly positive at the 5% level in explaining IMPACT of the NASD sample. At the bottom of Table 3, we report the p-value of the test that both Abs(DLLP) and lagged Abs(DLLP) are jointly indistinguishable from zero. The test rejects the hypothesis that unexplained provisioning has no effect on TOVER and VOL for both the NYSE and NASD banking firms, as well as on IMPACT for NASD firms.

The subperiod analyses of unexplained provisioning and bank opacity are reported in Table A.4. Focusing on the bottom row of panel A, during the pre-crisis period, unexplained provisioning is found to have significant effects on AS, ESPREAD, and TOVER of NYSE banking firms, and on TOVER, IMPACT, and VOL of NASD firms. During the financial crisis, panel B shows that unexplained provisioning has significant effect on TOVER of NASD firms, and on VOL of both NYSE and NASD firms. While unexplained provisioning seems to have significant effects on bank opacity, the results are sensitive to the choice of opacity measures and sampling periods.

4.2. *Delays in loss recognition and bank opacity*

Table A.5 reports the summary statistics of estimating the delays in loss recognition by comparing the adjusted R^2 of the two rolling regressions in Eqs. (3.3) and (3.4). For the full sampling period, the average increase in adjusted R^2 by including future nonperforming loans to explain current loan loss provisions is about 6 to 7 percentage points for both NYSE and NASD banking firms. For the two different subperiods, the changes in R^2 on balance went up from before the financial crisis to during the financial crisis. The distributions of the R^2 differences indicate that NASD banking firms exhibited somewhat bigger increases in R^2 than their NYSE counterparts.

Results from estimating the effects of delays in loss recognition on bank opacity are reported in Tables A.6 (for the full period) and A.7. (for the two subperiods). Over the full sampling period, NASD banking firms that recognize expected future losses more timely, as measured by LowDELR, are found to have statistically significantly lower AS and ESPREAD, suggesting that delays in loss recognition tend to increase opacity. However, LowDELR has a significantly positive coefficient in explaining TOVER of NASD banking firms and VOL of NYSE banking firms.

The effects on bank opacity from delays in recognizing loan loss also seem to be sensitive to the estimation period. The results in panel A of Table A.7 indicate that before the financial crisis, the coefficient of LowDELR is mostly insignificant, except for the VOL regression using the NYSE sample. However, during the financial crisis, the results in panel B of Table A.7 show that LowDELR has a significantly negative effect on AS and ESPREAD for both NYSE and NASD banking firms; LowDELR has a significantly negative effect on IMPACT for the NYSE sample which includes the largest banking firms. (LowDELR is insignificant in both the TOVER and the VOL regressions during the financial crisis). The findings provide confirming evidence that delay in loss recognition during the financial crisis raises bank opacity, which perhaps exacerbates the financial instability. This validates the concerns raised by the Financial Crisis Advisory Group.

5. Conclusions

Does how banks manage their loan loss reserves have an impact on their transparency? The answer seems to be yes. Discretionary actions by bank management, as indicated by unexplained loan loss provision derived from a statistical model, are found to have a significant effect on bank opacity. Furthermore, when discretion is measured by the extent to which future loan losses are recognized today, delays in recognizing loan loss are also found to have a significant effect on bank opacity. However, the results are sensitive to the choice of opacity measures and sampling period.

While it seems clear that how banking firms' provision for loan and lease losses has an impact on their transparency, the transmission mechanism from reserve practices to opacity is less straightforward and warrants additional research. For example, why different measures of opacity were affected differently by the discretion in reserve practices at different times? During the financial crisis, delay in recognizing loss contributes significantly to bank opacity; but why such a delay does not seem to have a significant effect on opacity during more tranquil times? One possible reason is that our construction of LowDELR may be rather crude in measuring delay during periods of normal loan losses. Another reason is that our measures of bank opacity did not move much during tranquil times, making the statistical relations difficult to detect. Nevertheless, unexplained loan loss provision is found to have significant effects on opacity even before the financial crisis.

Finally, since how banks account for reserves matters in determining their transparency, our results have clear policy implication for financial stability. To enhance transparency in banking, both promptly recognizing potentially impaired loans and improving the predictability of loan loss provisioning would be beneficial.

Acknowledgment

We thank Mark Flannery and Mahendrarajah Nimalendran for providing the microstructure data, Kevin Cook for excellent research assistance, and Anita Todd for editorial assistance. Remaining errors are ours. We are very grateful to CAREFIN for providing financial assistance for this research. Views in this paper are the authors' only and do not necessarily represent the views of the Federal Reserve Bank of San Francisco or the Federal Reserve System.

Appendix A. Variable Definitions

Earnings management and delays in loss recognition regressions:

LLP: Loan loss provisions as a percentage of total loans.

A: Total assets.

Ln(A): Natural log of total assets.

ΔNPL: Change in nonperforming loans (loans past due 90 days or more and still accruing interest and loans in nonaccrual status) as a percentage of total loans.
ALLL: Loan loss allowance as a percentage of total loans.
LoanR: Real estate loans as a percentage of total loans.
LoanC: Commercial and industrial loans as a percentage of total loans.
LoanD: Loans to depository institutions as a percentage of total loans.
LoanA: Agriculture loans as a percentage of total loans.
LoanI: Consumer loans as a percentage of total loans.
LoanF: Loans to foreign governments as a percentage of total loans.
Capital: Tier 1 regulatory capital ratio.
EBLLP: Earnings before loan loss provision and taxes divided by lagged total loans.

Microstructure regressions:

AS: Average adverse selection cost of trading stock, as a percentage of the share price.
ESPREAD: Average effective spread for transactions, as a percentage of the share price.
TOVER: The number of shares traded, divided by the average number of shares outstanding during the quarter.
IMPACT: An estimate of the permanent effect, or impact, of a trade on share price (Kyle 1985).
VOL: The annualized daily standard deviation of the continuously compounded returns between adjacent trades, computed using the quote midpoints.
DLLP: The error term that results from regressing LLP on ln(A), NPL, ALLL, LoanR, LoanC, LoanD, LoanA, LoanI, LoanF, and a constant, with quarterly dummies and bank fixed effects (Eq. (1)).
Abs(DLLP): The absolute value of DLLP.
LowDELR: (Low delayer) One if the bank is above the median change in R^2 at that quarter, and zero otherwise. The change in R^2 is computed as the difference between the adjusted R^2 of two regressions of LLP where one regression includes current and future changes in nonperforming loans as additional explanatory variables (Eqs. (3) and (4)).
MVLEV: Sum of book value of liabilities at the end of quarter t plus market value of equity at the end of quarter $t-1$, divided by market value of equity at $t-1$.
PINV: The inverse of PRICE, the quarterly average share price.
Ln(MVEQ): Natural log of MVEQ, the market value of common equity at the end of the quarter.

Table A.1. Descriptive statistics.

Panel A: Summary statistics for variables in the loan loss provision regression and delays in loss recognition regression, 1994–2009.

	NYSE sample						NASD sample					
	N	Mean	Std. dev.	Min.	Max.	Median	N	Mean	Std. dev.	Min.	Max.	Median
LLP	4416	0.164	0.285	−1.259	5.513	0.091	15,141	0.133	0.273	−3.717	5.967	0.071
A[a]	4420	81.815	239.131	0.159	2358.266	12.305	15,142	3.477	7.743	0.126	119.764	1.308
Ln(A)	4420	16.327	2.058	11.979	21.581	16.326	15,142	14.255	1.125	11.745	18.601	14.084
ΔNPL	4420	0.047	0.430	−5.246	6.981	0.009	15,142	0.068	0.509	−12.827	13.790	0.010
ALLL	4420	1.592	0.791	0.000	7.778	1.415	15,142	1.440	0.592	−1.474	7.388	1.323
LoanR	4420	58.133	22.577	0.000	100.084	60.805	15,142	70.600	16.859	0.000	101.598	72.849
LoanC	4420	20.652	13.753	0.000	96.471	17.730	15,142	17.013	11.779	0.000	100.000	14.772
LoanD	4420	0.748	2.390	0.000	33.823	0.004	15,142	0.119	1.171	0.000	45.010	0.000
LoanA	4420	0.534	1.165	0.000	12.857	0.107	15,142	1.018	2.227	0.000	20.910	0.073
LoanI	4420	8.586	12.368	0.000	97.227	3.351	15,142	5.813	9.005	0.000	66.292	0.826
LoanF	4420	0.105	0.471	0.000	6.586	0.000	15,142	0.013	0.179	0.000	5.372	0.000
Capital[b]	2616	0.118	0.096	0.012	1.506	0.105	9,553	0.120	0.047	0.001	1.283	0.112
EBLLP[b]	2616	0.022	0.156	−0.378	3.796	0.009	9,553	0.007	0.028	−0.259	1.194	0.007

Note: [a]in $ billions; [b]data begin in 1999.

Table A.1. (*Continued*)

Panel B: Summary statistics for variables in the opacity regressions, 1994–2009.

	NYSE sample						NASD sample					
	N	Mean	Std. dev.	Min.	Max.	Median	N	Mean	Std. dev.	Min.	Max.	Median
AS	4420	0.772	0.902	0.010	6.126	0.430	15,141	1.416	1.099	0.024	6.529	1.167
ESPREAD	4420	0.534	0.636	0.032	5.855	0.298	15,142	1.509	1.169	0.043	9.074	1.265
TOVER	4420	0.387	0.533	0.014	7.399	0.257	15,142	0.194	0.300	0.012	7.399	0.107
IMPACT	4420	13.410	13.312	0.833	155.600	8.613	15,142	23.109	19.009	0.000	215.340	19.340
VOL	4420	68.246	55.375	5.874	368.558	47.245	15,142	40.333	44.978	0.000	377.478	24.879
DLLP	4416	0.000	0.208	−1.667	4.933	−0.011	15,141	0.000	0.218	−3.979	5.180	−0.008
Abs(DLLP)	4416	0.096	0.184	0.000	4.933	0.052	15,141	0.099	0.194	0.000	5.180	0.053
LowDELR[a]	2616	0.529	0.499	0.000	1.000	1.000	9,553	0.491	0.500	0.000	1.000	0.000
MVLEV	4420	8.085	6.448	1.283	122.479	6.702	15,142	8.871	6.049	1.283	122.479	7.385
PRICE	4420	34.954	21.332	2.080	180.590	30.570	15,142	23.252	12.457	2.080	180.590	21.380
PINV	4420	0.043	0.038	0.006	0.481	0.033	15,142	0.059	0.046	0.006	0.481	0.047
MVEQ[b]	4420	9.754	19.018	0.013	131.646	2.181	15,142	0.606	1.807	0.008	39.317	0.185
Ln(MVEQ)	4420	14.473	2.074	9.495	18.696	14.595	15,142	12.275	1.284	8.979	17.487	12.126

Note: [a]data begin in 1999; [b]in $ billions.

Table A.2. Regression estimates of loan loss provisions.

The dependent variable is LLP, loan loss provisions as a percentage of total loans. Detailed description of explanatory variables is in Appendix A. Bank fixed effect and quarter time dummies are included in all regressions but their coefficients are not reported. Robust standard errors are in parentheses.

Dependent variable: LLP			
Period:	1994–2009	1994:Q1-2007:Q2	2007:Q3-2009:Q4
Ln(A)	0.052[a]	0.034[b]	−0.330[a]
	(0.014)	(0.014)	(0.111)
ΔNPL	0.085[a]	0.041[b]	0.082[a]
	(0.013)	(0.017)	(0.018)
Lagged ALLL	0.113[a]	0.023[c]	0.202[a]
	(0.015)	(0.014)	(0.031)
LoanR	−0.001	−0.001	−0.003
	(0.001)	(0.001)	(0.005)
LoanC	0.002	0.002	−0.005
	(0.001)	(0.001)	(0.007)
LoanD	−0.006[b]	−0.008[c]	0.002
	(0.003)	(0.005)	(0.009)
LoanA	−0.003	−0.007	0.024
	(0.005)	(0.005)	(0.020)
LoanI	−0.000	−0.001	−0.008[a]
	(0.001)	(0.001)	(0.002)
LoanF	−0.029	−0.010	0.041
	(0.020)	(0.018)	(0.028)
Constant	−0.378[c]	−0.393[c]	5.539[a]
	(0.210)	(0.205)	(1.828)
Adj-R^2	0.360	0.215	0.452
N	19557	16663	2894

Notes: [a], [b] and [c] indicate significance at 1%, 5%, and 10% levels, respectively.

Table A.3. Effects of discretionary provision on bank opacity, 1994–2009.

The dependent variable is one of five measures of opacity. Detailed variable description is in the Appendix A. Quarter fixed effects are included in all regressions but are not reported. Robust standard errors are in parentheses. The bottom row reports the p-value of testing the hypothesis H_0 that both Abs (DLLP) and lagged Abs (DLLP) are jointly indistinguishable from zero.

Dep. Var.:	AS		ESPREAD		TOVER		IMPACT		VOL	
Exchange:	NYSE	NASD	NYSE	NASD	NYSE	NASD	NYSE	NASD	NYSE	NASD
Abs (DLLP)	0.052	−0.027	0.054	0.009	0.171[b]	0.063[a]	0.620	1.015	12.718[b]	7.394[a]
	(0.080)	(0.057)	(0.049)	(0.071)	(0.069)	(0.021)	(0.824)	(0.782)	(4.976)	(2.431)
lagged Abs (DLLP)	0.143	−0.016	0.168[c]	0.005	0.191[b]	0.121[a]	0.775	2.223[b]	4.754	10.314[a]
	(0.087)	(0.073)	(0.090)	(0.086)	(0.075)	(0.039)	(0.912)	(0.881)	(4.034)	(2.388)
MVLEV	−0.007[c]	0.005	−0.001	0.015[b]	0.016[b]	0.007[a]	0.204[b]	−0.021	0.265	−0.278[c]
	(0.004)	(0.005)	(0.003)	(0.006)	(0.007)	(0.003)	(0.090)	(0.059)	(0.435)	(0.157)
PINV	2.849[a]	0.395	3.845[a]	2.255[a]	1.509[c]	0.499	−48.810[b]	-29.242[a]	414.295[a]	132.087[a]
	(1.022)	(0.725)	(0.942)	(0.831)	(0.855)	(0.323)	(18.771)	(9.597)	(70.050)	(23.181)
Ln(MVEQ)	−0.254[a]	−0.558[a]	−0.172[a]	−0.537[a]	0.085[a]	0.099[a]	−3.849[a]	−4.552[a]	10.266[a]	9.674[a]
	(0.021)	(0.027)	(0.017)	(0.026)	(0.009)	(0.010)	(0.316)	(0.210)	(1.046)	(0.845)
Constant	4.590[a]	8.476[a]	2.859[a]	8.057[a]	−1.254[a]	−1.210[a]	61.077[a]	60.167[a]	−144.003[a]	−121.238[a]
	(0.361)	(0.359)	(0.258)	(0.348)	(0.170)	(0.158)	(5.132)	(2.977)	(18.094)	(11.329)
Adj-R^2	0.517	0.601	0.593	0.600	0.576	0.287	0.560	0.653	0.557	0.674
N	4106	13437	4106	13438	4106	13438	4106	13438	4106	13438
p-value of H_0	0.219	0.889	0.177	0.992	0.018	0.001	0.680	0.042	0.039	0.000

Notes: [a], [b], and [c] indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A.4. Effects of discretionary provision on bank opacity, by subperiod.

The dependent variable is one of five measures of opacity. Detailed variable description is in the Appendix A. Quarter fixed effects are included in all regressions but are not reported. Robust standard errors are in parentheses. The bottom row reports the p-value of testing the hypothesis H0 that both Abs (DLLP) and lagged Abs (DLLP) are jointly indistinguishable from zero.

Panel A: 1994:Q1-2007:Q2

Dep. Var.:	AS		ESPREAD		TOVER		IMPACT		VOL	
Exchange:	NYSE	NASD	NYSE	NASD	NYSE	NASD	NYSE	NASD	NYSE	NASD
Abs (DLLP)	0.096	0.027	0.108[a]	0.020	0.108[a]	0.030	0.976	0.805	9.640[b]	0.991
	(0.083)	(0.063)	(0.030)	(0.071)	(0.028)	(0.019)	(0.882)	(0.967)	(3.896)	(1.447)
lagged Abs (DLLP)	0.171[b]	0.090	0.218[a]	0.104	0.073[a]	0.061	1.205	2.559[b]	9.403[b]	5.443[a]
	(0.079)	(0.093)	(0.065)	(0.101)	(0.021)	(0.038)	(0.940)	(1.092)	(3.988)	(1.910)
MVLEV	−0.009	−0.010[c]	0.015[b]	−0.007	0.008[b]	0.005[a]	0.090	−0.052	−0.061	0.247[b]
	(0.009)	(0.006)	(0.007)	(0.006)	(0.004)	(0.001)	(0.106)	(0.079)	(0.477)	(0.097)
PINV	4.430[a]	1.937[b]	5.745[a]	3.840[a]	0.590	0.605[a]	−41.180[a]	−27.315[a]	520.826[a]	168.653[a]
	(1.212)	(0.834)	(0.963)	(0.834)	(0.456)	(0.141)	(14.401)	(8.938)	(70.209)	(14.130)
Ln (MVEQ)	−0.249[a]	−0.476[a]	−0.147[a]	−0.443[a]	0.048[a]	0.049[a]	−3.173[a]	−3.738[a]	12.789[a]	6.920[a]
	(0.021)	(0.022)	(0.014)	(0.020)	(0.005)	(0.005)	(0.244)	(0.197)	(0.807)	(0.564)
Constant	4.482[a]	7.662[a]	2.288[a]	6.913[a]	−0.599[a]	−0.548[a]	51.874[a]	50.490[a]	−181.695[a]	−93.571[a]
	(0.400)	(0.323)	(0.235)	(0.295)	(0.090)	(0.073)	(4.109)	(2.984)	(13.623)	(7.779)
Adj-R^2	0.518	0.615	0.667	0.637	0.301	0.208	0.507	0.616	0.540	0.517
N	3560	11146	3560	11147	3560	11147	3560	11147	3560	11147
p-value of H_0	0.013	0.626	0.000	0.571	0.000	0.094	0.442	0.049	0.026	0.014

Notes: [a], [b], and [c] indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A.4. (*Continued*)

Panel B: 2007:Q3-2009:Q4										
Dep. Var.:	AS		ESPREAD		TOVER		IMPACT		VOL	
Exchange:	NYSE	NASD	NYSE	NASD	NYSE	NASD	NYSE	NASD	NYSE	NASD
Abs(DLLP)	−0.104	−0.073	−0.093	0.080	0.311	0.113[b]	−1.107	1.570	31.582[a]	15.389[a]
	(0.112)	(0.082)	(0.116)	(0.121)	(0.320)	(0.048)	(2.465)	(1.349)	(11.115)	(4.337)
lagged Abs (DLLP)	−0.063	−0.136[c]	−0.027	−0.054	0.351	0.203[a]	3.279	0.608	19.833[c]	19.277[a]
	(0.141)	(0.079)	(0.154)	(0.123)	(0.345)	(0.066)	(3.012)	(1.302)	(10.733)	(4.307)
MVLEV	0.003	−0.000	0.003	0.007	0.018[b]	0.021[a]	0.158[c]	−0.207[b]	0.379	0.480[b]
	(0.004)	(0.005)	(0.004)	(0.008)	(0.009)	(0.004)	(0.084)	(0.088)	(0.355)	(0.203)
PINV	−1.041	−2.572[a]	−0.510	−1.260	3.735[c]	0.266	−58.612[b]	−33.549[c]	167.388[c]	68.864[c]
	(1.173)	(0.888)	(1.176)	(1.277)	(2.161)	(0.634)	(26.431)	(17.962)	(98.714)	(40.543)
Ln (MVEQ)	−0.241[a]	−1.084[a]	−0.231[a]	−1.182[a]	0.288[a]	0.414[a]	−8.145[a]	−9.616[a]	−3.145	30.147[a]
	(0.042)	(0.070)	(0.046)	(0.079)	(0.036)	(0.044)	(0.808)	(0.618)	(3.156)	(2.842)
Constant	3.894[a]	14.964[a]	3.769[a]	16.005[a]	−3.081[a]	−4.881[a]	145.848[a]	175.958[a]	153.770[a]	−247.260[a]
	(0.700)	(0.903)	(0.760)	(1.014)	(0.499)	(0.565)	(14.278)	(8.666)	(52.448)	(36.970)
Adj-R^2	0.481	0.687	0.427	0.668	0.438	0.500	0.636	0.386	0.456	0.518
N	484	2036	484	2036	484	2036	484	2036	484	2036
p-value of H_0	0.647	0.228	0.691	0.533	0.340	0.002	0.438	0.503	0.013	0.000

Notes: [a], [b], and [c] indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A.5. Summary Statistics for estimating the delay in loss recognition regressions.

Regression 1 is as follows:

$$\begin{aligned}\mathrm{LLP}_t = {} & \beta_0 + \beta_1 \Delta\mathrm{NPL}_{t-1} + \beta_2 \Delta\mathrm{NPL}_{t-2} + \beta_3 \mathrm{Capital}_{t-1} \\ & + \beta_4 \mathrm{EBLLP}_t + \beta_5 \ln(A_{t-1}) + \varepsilon_t.\end{aligned}$$

Regression 2 is as follows:

$$\begin{aligned}\mathrm{LLP}_t = {} & \beta_0 + \beta_1 \Delta\mathrm{NPL}_{t-1} + \beta_2 \Delta\mathrm{NPL}_{t-2} + \beta_3 \Delta\mathrm{NPL}_t + \beta_4 \Delta\mathrm{NPL}_{t+1} + \beta_5 \mathrm{Capital}_{t-1} \\ & + \beta_6 \mathrm{EBLLP}_t + \beta_7 \ln(A_{t-1}) + \varepsilon_t.\end{aligned}$$

Detailed variable description is in Appendix A.

	Mean	Median	Q1	Q3	Std. Dev.
NYSE BHCs			1999–2009		
Adj-R^2 regression 1	0.406	0.471	0.122	0.764	0.413
Adj-R^2 regression 2	0.474	0.607	0.241	0.828	0.463
Difference	0.068	0.021	−0.078	0.181	0.293
NASD BHCs			1999–2009		
Adj-R^2 regression 1	0.365	0.426	0.096	0.689	0.397
Adj-R^2 regression 2	0.424	0.545	0.162	0.787	0.458
Difference	0.059	0.011	−0.115	0.185	0.305
NYSE BHCs			1999:Q1-2007:Q2		
Adj-R^2 regression 1	0.375	0.425	0.068	0.733	0.417
Adj-R^2 regression 2	0.442	0.563	0.191	0.799	0.463
Difference	0.067	0.016	−0.085	0.183	0.301
NASD BHCs			1999:Q1-2007:Q2		
Adj-R^2 regression 1	0.339	0.391	0.065	0.661	0.397
Adj-R^2 regression 2	0.383	0.490	0.104	0.753	0.459
Difference	0.044	−0.001	−0.131	0.168	0.305
NYSE BHCs			2007:Q3-2009:Q4		
Adj-R^2 regression 1	0.542	0.669	0.349	0.824	0.364
Adj-R^2 regression 2	0.615	0.785	0.466	0.915	0.435
Difference	0.073	0.039	−0.040	0.175	0.254
NASD BHCs			2007:Q3-2009:Q4		
Adj-R^2 regression 1	0.451	0.535	0.204	0.762	0.384
Adj-R^2 regression 2	0.559	0.703	0.354	0.886	0.429
Difference	0.108	0.049	−0.056	0.242	0.298

Table A.6. Effects of delay in loss recognition on bank opacity, 1999–2009.

The dependent variable is one of five measures of opacity. Detailed variable description is in the Appendix. Quarter fixed effects are included in all regressions but not reported. Robust standard errors are in parentheses.

Dep. Var.:	AS		ESPREAD		TOVER		IMPACT		VOL	
Exchange:	NYSE	NASD	NYSE	NASD	NYSE	NASD	NYSE	NASD	NYSE	NASD
LowDELR	−0.011	−0.047[b]	−0.027	−0.049[c]	−0.006	0.016[b]	−0.192	−0.111	4.518[c]	1.345
	(0.043)	(0.023)	(0.027)	(0.025)	(0.020)	(0.007)	(0.542)	(0.342)	(2.406)	(0.900)
MVLEV	−0.002	0.009	−0.000	0.017[b]	0.019[b]	0.010[a]	0.175	−0.101	0.251	−0.184
	(0.004)	(0.006)	(0.004)	(0.007)	(0.009)	(0.003)	(0.117)	(0.066)	(0.538)	(0.184)
PINV	1.114	−0.699	2.899[a]	1.336	2.095[c]	0.211	−32.206	−18.143	429.031[a]	141.217[a]
	(1.463)	(0.846)	(1.015)	(1.027)	(1.219)	(0.407)	(23.318)	(11.373)	(81.737)	(29.841)
Ln (MVEQ)	−0.256[a]	−0.591[a]	−0.175[a]	−0.576[a]	0.097[a]	0.132[a]	−4.289[a]	−5.916[a]	11.030[a]	12.188[a]
	(0.025)	(0.035)	(0.020)	(0.033)	(0.011)	(0.013)	(0.354)	(0.243)	(1.334)	(1.144)
Constant	4.422[a]	8.836[a]	3.019[a]	8.673[a]	−1.401[a]	−1.661[a]	73.587[a]	87.379[a]	−144.985[a]	−145.014[a]
	(0.391)	(0.453)	(0.317)	(0.440)	(0.195)	(0.177)	(5.833)	(3.385)	(22.451)	(14.922)
Adj-R^2	0.477	0.608	0.535	0.605	0.568	0.330	0.554	0.563	0.427	0.636
N	2616	9553	2616	9553	2616	9553	2616	9553	2616	9553

Notes: [a], [b], and [c] indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A.7. Effects of delay in loss recognition on bank opacity, by subperiod.

The dependent variable is one of five measures of opacity. Detailed variable description is in Appendix A. Quarter fixed effects are included in all regressions but not reported. Robust standard errors are in parentheses.

Panel A: 1999–2007:Q2

Dep. Var.:	AS		ESPREAD		TOVER		IMPACT		VOL	
Exchange:	NYSE	NASD	NYSE	NASD	NYSE	NASD	NYSE	NASD	NYSE	NASD
LowDELR	0.023	−0.005	−0.003	−0.004	−0.010	0.000	0.659	−0.020	5.084[c]	−0.150
	(0.050)	(0.020)	(0.023)	(0.019)	(0.011)	(0.004)	(0.439)	(0.338)	(2.968)	(0.636)
MVLEV	0.001	−0.005	0.025[b]	−0.006	0.000	0.006[a]	0.005	−0.234[b]	−0.099	0.154
	(0.016)	(0.007)	(0.012)	(0.007)	(0.006)	(0.001)	(0.189)	(0.110)	(0.947)	(0.151)
PINV	2.827	0.994	5.142[a]	3.307[a]	0.637	0.532[a]	−23.047	−14.354	594.174[a]	221.978[a]
	(1.944)	(1.105)	(1.109)	(1.137)	(0.740)	(0.171)	(16.052)	(13.600)	(74.534)	(22.444)
Ln(MVEQ)	−0.251[a]	−0.478[a]	−0.141[a]	−0.447[a]	0.046[a]	0.067[a]	−3.429[a]	−5.133[a]	14.718[a]	8.528[a]
	(0.026)	(0.028)	(0.015)	(0.025)	(0.006)	(0.006)	(0.258)	(0.247)	(0.933)	(0.796)
Constant	4.258[a]	7.392[a]	2.285[a]	7.076[a]	−0.477[a]	−0.816[a]	60.986[a]	78.112[a]	−203.391[a]	−103.595[a]
	(0.459)	(0.383)	(0.265)	(0.351)	(0.100)	(0.085)	(4.755)	(3.628)	(16.684)	(10.739)
Adj-R^2	0.474	0.608	0.620	0.639	0.249	0.306	0.496	0.460	0.442	0.430
N	2128	7297	2128	7297	2128	7297	2128	7297	2128	7297

Notes: [a,b,] and [c] indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A.7. (*Continued*)

Panel B: 2007:Q3-2009:Q4

Dep. Var.:	AS		ESPREAD		TOVER		IMPACT		VOL	
Exchange:	NYSE	NASD	NYSE	NASD	NYSE	NASD	NYSE	NASD	NYSE	NASD
LowDELR	−0.139[c]	−0.129[b]	−0.161[c]	−0.127[c]	0.052	0.034	−4.087[b]	0.076	2.614	3.273
	(0.076)	(0.056)	(0.085)	(0.069)	(0.084)	(0.024)	(1.787)	(0.920)	(4.734)	(2.632)
MVLEV	0.001	0.001	−0.000	0.009	0.021[b]	0.020[a]	0.143	−0.173[b]	0.470	0.538[b]
	(0.004)	(0.006)	(0.004)	(0.008)	(0.009)	(0.004)	(0.096)	(0.084)	(0.341)	(0.212)
PINV	−0.988	−2.840[a]	−0.137	−1.271	4.493[b]	0.324	−51.590[c]	−28.469[c]	165.876	117.124[a]
	(1.284)	(0.878)	(1.382)	(1.220)	(2.074)	(0.574)	(29.523)	(15.801)	(106.130)	(39.176)
Ln(MVEQ)	−0.245[a]	−1.049[a]	−0.244[a]	−1.122[a]	0.268[a]	0.390[a]	−8.235[a]	−9.503[a]	−3.002	31.123[a]
	(0.044)	(0.069)	(0.048)	(0.076)	(0.035)	(0.040)	(0.806)	(0.568)	(3.056)	(2.858)
Constant	4.006[a]	14.619[a]	4.005[a]	15.357[a]	−2.807[a]	−4.557[a]	148.449[a]	174.269[a]	157.394[a]	−260.657[a]
	(0.733)	(0.898)	(0.797)	(0.984)	(0.484)	(0.523)	(14.189)	(7.931)	(51.579)	(36.801)
Adj-R^2	0.485	0.680	0.439	0.662	0.464	0.483	0.643	0.421	0.396	0.518
N	488	2256	488	2256	488	2256	488	2256	488	2256

Notes: [a], [b], and [c] indicate significance at the 1%, 5%, and 10% levels, respectively.

References

A. S. Ahmed, C. Takeda & S. Thomas (1999) Bank loan loss provisions: A reexamination of capital management, earnings management and signaling effects, *Journal of Accounting and Economics* **28**, 1–25.

G. Akerlof (1970) The market for 'lemons': Quality uncertainty and the market mechanism, *Quarterly Journal of Economics* **84**, 488–500.

Y. Amihud (2002) Illiquidity and stock returns: Cross-section and time series effects, *Journal of Financial Markets* **5**, 31–56.

A. Beatty, S. Chamberlain & J. Magliolo (1995) Managing financial reports of commercial banks: The influence of taxes, regulatory capital and earnings, *Journal of Accounting Research* **33**, 231–262.

A. Beatty & S. Liao (2011) Regulatory capital ratios, loan loss provisioning and procyclicality, *Journal of Accounting and Economics* **52**, 1–20.

A. L. Beatty, B. Ke & K. R. Petroni (2002) Earnings management to avoid earnings declines across publicly and privately held banks, *The Accounting Review* **77**, 547–570.

W. Beaver & E. Engel (1996) Discretionary behavior with respect to allowances for loan losses and the behavior of security prices, *Journal of Accounting and Economics* **22**, 177–206.

D. Bergstresser & T. Philippon (2006) CEO incentives and earnings management, *Journal of Financial Economics* **80**, 511–529.

D. Bergstresser, M. Desai & J. Rauh (2006) Earnings manipulation, pension assumptions, and managerial investment decisions, *Quarterly Journal of Economics* **121**, 157–195.

H. Bessembinder, K. Chan & P. Seguin (1996) An empirical examination of information, differences of opinion, and trading activity, *Journal of Financial Economics* **40**, 105–134.

M. Brennan & A. Subrahmanyam (1995) Investment analysis and price formation in securities markets, *Journal of Financial Economics* **38**, 361–381.

R. M. Bushman & C. D. Williams (2012) Delayed expected loss recognition and the risk profile of banks, Kenan-Flager Business School, mimeo.

M. M. Cornett, A. J. Marcus & H. Tehranian (2008) Corporate governance and pay-for performance: The impact of earnings management, *Journal of Financial Economics* **87**, 357–373.

M. M. Cornett, J. J. McNutt & H. Tehranian (2009) Corporate governance and earnings management at large U.S. bank holding companies, *Journal of Corporate Finance* **15**, 412–430.

A. Desai, M. Nimalendran & S. Venkataraman (1998) Changes in trading activity following stock splits and their effect on volatility and the adverse-information component of the bid-ask spread, *Journal of Financial Research* **21**, 159–183.

Financial Accounting Standards Board (2012) Proposed Accounting Standards Update Financial Instruments – Credit Losses. Financial Accounting Series Exposure Draft.

M. J. Flannery, S. H. Kwan & M. Nimalendran (2004) Market evidence on the opaqueness of banking firms' assets, *Journal of Financial Economics* **71**, 419–460.

M. J. Flannery, S. H. Kwan & M. Nimalendran (2013) The 2007-09 financial crisis and bank opaqueness, *Journal of Financial Intermediation* **22**, 55–84.

T. George, G. Kaul & M. Nimalendran (1991) Estimation of the bid-ask spread and its components: A new approach, *Review of Financial Studies* **4**, 623–656.

G. Gorton & G. Pennacchi (1990) Financial-intermediaries and liquidity creation, *Journal of Finance* **45**, 49–71.

B. J. Hall & J. B. Liebman (1998) Are CEOs really paid like bureaucrats? *The Quarterly Journal of Economics* **113**, 653–691.

M. Harris & A. Raviv (1993) Differences of opinion make a horse race, *Review of Financial Studies* **6**, 473–506.

P. Healy (1985) The effect of bonus schemes on accounting decisions, *Journal of Accounting and Economics* **7**, 85–107.

P. M. Healy & J. M. Wahlen (1999) A review of the earnings management literature and its implications for standard setting, *Accounting Horizons* **13**, 365–383.

F. Heider, M. Hoerova & C. Holthausen (2009) Liquidity hoarding and interbank market spreads: The role of counterparty risk. Discussion Paper 2009-40 S, Tilburg University, Center for Economic Research.

B. Hirtle (2006) Stock market reaction to financial statement certification by bank holding company CEOs, *Journal of Money, Credit, and Banking* **38**, 1263–1291.

G. Iannotta (2006) Testing for opaqueness in the European banking industry: Evidence from bond credit ratings, *Journal of Financial Services Research* **30**, 287–309.

J. S. Jones, W. Y. Lee & T. J. Yeager (2012) Opaque banks, price discovery, and financial instability, *Journal of Financial Intermediation* **21**, 383–408.

I. Krinsky & J. Lee (1996) Earnings announcements and the components of the bid-ask spread, *Journal of Finance* **51**, 1523–1535.

S. Kwan (2010) Financial crisis and bank lending, Federal Reserve Bank of San Francisco Working Paper.

A. Kyle (1985) Continuous auctions and insider trading, *Econometrica* **53**, 1315–1335.

C. M. C. Lee & M. J. Ready (1991) Inferring trade direction from intraday data, *Journal of Finance* **46**, 733–746.

A. Madhavan (2000) Market microstructure: A survey, *Journal of Financial Markets* **3**, 205–258.

D. Morgan (2002) Rating banks: Risk and uncertainty in an opaque industry, *American Economic Review* **92**, 874–888.

M. Pritsker (2010) Informational Easing: Improving credit conditions through the release of information, *Federal Reserve Bank of New York Economic Policy Review* **16**, 77–87.