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Predicting Credit Losses: Loan Fair Values versus Historical Costs

Brett W. Cantrell
The University of Mississippi

John M. McInnis
Christopher G. Yust
The University of Texas at Austin

ABSTRACT: Standard-setters and many investors argue that loan fair values provide more useful information about credit losses than historical cost information, while bankers and others generally disagree. We examine the ability of reported loan fair values to predict credit losses relative to the ability of net historical costs currently recognized under U.S. GAAP. Our analysis is important because credit losses in the banking sector can have severe and widespread economic effects, as the recent financial crisis demonstrates. Overall, we find that net historical loan costs are a better predictor of credit losses than reported loan fair values. Specifically, we find that historical cost information is more useful in predicting future net chargeoffs, non-performing loans, and bank failures over both short and long time horizons. Further tests indicate that the relative predictive ability of reported loan fair values improves in higher scrutiny environments, suggesting that a lack of scrutiny over reported loan fair values may contribute to our findings.

Keywords: *fair value*; *loans*; *historical cost*; *chargeoffs*; *impairments*; *credit loss*; *bank failure*.

Data Availability: *Data are available from sources identified in the text.*

I. INTRODUCTION

Bank practitioners indicate that managing the credit risk of loan customers "is the most important aspect of the banking business model" (American Bankers Association [ABA] 2010). Loans account for the majority of assets in the banking industry and, as the recent

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financial crisis demonstrates, credit losses related to loans can have a significant detrimental impact on the broad economy. Despite the importance of predicting credit losses, there is a lack of consensus as to whether measuring loans at fair value or net historical cost provides the most useful information for assessing credit risk (Leone 2008). In this study, we examine the ability of reported loan fair values versus net historical costs to predict credit losses related to loans.

Under U.S. GAAP, bank loans not held for sale (hereafter, bank loans) are currently reported on the balance sheet at amortized historical cost, net of a loan loss reserve for uncollectibility. However, SFAS 107 (Financial Accounting Standards Board [FASB] 1991, now codified in ASC 825-10) requires banks to disclose the fair value of their loan portfolios in the notes to the financial statements. In recent years, many commentators, including U.S. standard-setters and investors, have advocated the recognition of loans and other financial instruments at fair value, which is the hypothetical price that could be obtained in an orderly sale (FASB 2010). Supporters of this approach contend that the fair value of loans is the most relevant measurement attribute for assessing credit risk (FASB 2010; Trott 2009; Linsmeier 2011). The intuition behind this argument is that fair values reflect market prices or other market-based inputs, and these market signals aggregate forward-looking information about credit risk from all available sources in the economy. Since market participants will pay more (less) for loans that are less (more) likely to be in default in the future, loan fair values can serve as a leading indicator of deterioration in loan credit quality (Novoa, Scarlata, and Sole 2009; Linsmeier 2011).

Supporters of measuring loans at fair value also point to weaknesses in the measurement of loans at net historical cost via the loan loss reserve. This reserve is regarded as backward-looking in the sense that credit impairments are typically based upon an "incurred loss" approach, where banks recognize only those credit impairments that are estimated to have already occurred (Trott 2009). This incurred loss approach can result in delays in expected loss recognition that can amplify the pro-cyclical capital effect during economic downturns (Beatty and Liao 2011). Further, a number of academic studies provide evidence that banks manage the loan loss reserve in an opportunistic fashion (Beatty, Chamberlain, and Magliolo 1995; Ahmed, Takeda, and Thomas 1999; Beatty, Ke, and Petroni 2002), which could also impair the ability of net historical costs to predict credit losses.

However, measuring loans at fair value has many critics, including bank practitioners and regulators. Perhaps the strongest objection is that active markets for most bank loans do not exist, so loan fair values have to be estimated using both market and non-market inputs. This subjective estimation process raises concerns about the reliability and usefulness of loan fair value measurements relative to historical cost measures (FASB 2007; ABA 2010). In addition, critics contend that loan fair values are irrelevant for assessing risk and performance since most loans are not sold prior to maturity (ABA 2010).

Given the competing arguments above, it is ultimately an empirical question as to whether reported loan fair values are relatively more or less useful than net historical costs in predicting credit losses. We use data from a large sample of banks both before and during the recent financial crisis to answer this question. We use machine-readable data from 2005 to 2009 to collect SFAS 107 loan fair value disclosures. Our sample captures a broad cross-section of U.S. banks and consists of all exchange-traded and OTC public banks, as well as several large private banks, over this time period.

For our initial prediction tests, we select two dependent variables directly related to credit losses, both of which have been used in prior work and are key fundamentals reported in the MD&A sections of SEC filings and bank regulatory filings. Our first dependent variable is future net chargeoffs, which is the amount of loans written off as uncollectible in a year, net of any recoveries. Our second dependent variable is future non-performing loans, which are loans that have either been restructured, are past due, or are no longer yielding accrued interest revenue.

We begin with "horse race" tests, in which net historical costs are used to predict future credit losses in one model and reported loan fair values are used in another model. The predictive ability of the two models is then compared. We conduct both in-sample tests, where the full sample is used to estimate model parameters, and out-of-sample tests, where data from prior and current years are used to estimate model parameters and a prediction is formed for year t+1. Overall, we find that models using reported loan fair values do not have better predictive ability for credit losses compared to models with net historical costs. In fact, in most tests, the fair value models fare significantly worse, using both levels and changes specifications. In addition, we conduct tests of the *incremental* predictive ability of reported loan fair values. In these tests, net historical costs are included in a single model along with the difference between loan fair values and net historical costs. We find no evidence that reported loan fair values provide meaningful incremental predictive ability for credit losses.

We also demonstrate that changes in market-wide interest rates unrelated to credit risk do not appear to handicap reported loan fair values in predicting future credit losses in our analysis. Further, we hand-collect a random sample of loan fair values back to 1994 to (1) accumulate credit losses multiple years into the future, and (2) assess the sensitivity of our findings to the time period examined. Overall, the results of these tests are consistent with our main findings. Reported loan fair values are a relatively poor predictor of future credit losses whether we accumulate credit losses over multiple future periods or examine a longer time period not affected by the financial crisis.

For our final prediction test, we examine whether reported loan fair values have an incremental ability to predict bank failures. Consistent with our tests on predicting chargeoffs and non-performing loans, we find no evidence that reported loan fair values are associated with the probability of a bank failure incremental to net historical costs. This finding is important because the Securities and Exchange Commission (SEC 2008) found that poor lending decisions and related credit losses were a precipitating factor in bank failures during the financial crisis. Overall, loans stated at net historical cost emerge as the winner in our empirical tests. Our findings indicate that reported loan fair values do not appear to provide users with a leading indicator of future credit losses, whether these losses are in the form of chargeoffs, non-performing loans, or bank failures.

Finally, we examine three reasons why reported loan fair values may perform relatively worse in predicting credit losses. One explanation is that loan fair values are inherently difficult to estimate because active selling markets for loans often do not exist and banks lack the experience or sophistication needed to estimate loan fair vales reliably. Another explanation is that managers use their discretion to manipulate loan fair values. The final explanation is that fair values are not scrutinized to the same extent as net historical costs, potentially because loan fair values are disclosed but not recognized, which leads management to put forth less effort in their estimation. We find that proxies for inherent estimation difficulty, experience in selling loans at fair value, and managerial manipulation incentives are not related to the relatively poor predictive ability of reported loan fair values. However, proxies for scrutiny in the form of Big N auditor, audit committee expertise, and analyst coverage are associated with increased predictive ability. Thus, we conclude that limited scrutiny over loan fair values likely contributes more to the relatively poor predictive ability of reported loan fair values than the other explanations.

This study makes important contributions to the literature. We provide timely evidence on the ability of loan fair value information to predict credit losses relative to the net historical cost values already reported on the balance sheet under current U.S. GAAP. Although prior work examines whether market participants price disclosed loan fair values, the evidence from these studies is mixed and does not provide direct evidence on the relation between fair value information and lending fundamentals related to credit quality. Our study provides this direct evidence and indicates reported loan fair values are a poor predictor of credit loss fundamentals relative to net historical cost information. Moreover, our analysis offers insights as to *why* reported loan fair values perform relatively poorly in predicting future credit losses.

Our results should interest policymakers in two ways. First, given the usefulness of net historical loan costs in predicting credit losses, our findings suggest that any new accounting standard for the reporting of bank loans should retain at least some measurement at net historical cost. This is consistent with recent standards proposals in this area (e.g., FASB 2010, 2013b) retaining historic cost measurement, at least in part. Second, improvements in the reliability of loan fair values are needed. Compared to net historical costs, loan fair values currently reported under U.S. GAAP are not particularly useful for understanding credit risk in banks' loan portfolios, suggesting that additional scrutiny of these figures is likely needed.

However, we caution readers that our study provides evidence only on the ability of currently *disclosed* loan fair values relative to net historical costs at predicting future credit losses. It is possible that loan fair values would perform differently if they are eventually required to be recognized in banks' financial statements. Further, although we conduct tests in different time periods and in various subsets of banks, the majority of our tests involve the broad cross-section of banks for the 2005 to 2009 period. It is possible that inferences may be different in different samples.

II. INSTITUTIONAL DETAILS AND PRIOR LITERATURE

Loan Accounting

Currently under U.S. GAAP, bank loans not held for sale are recorded at amortized historical cost less a loan loss reserve for uncollectibility.[1] Banks use considerable financial and nonfinancial information when computing the loan loss reserve.[2] Management typically assigns loans in the bank's portfolio to different ratings classes, which are standardized across the banking industry by the FDIC. Banks should consider the payment history of similar loans and borrowers' overall current financial position when assigning loans to different classifications. Generally, managers will also consider the appraised value and nature of any collateral, current economic conditions, or any other reasonable factors that could affect the collectability of the loan. Banks have considerable discretion over how individual loans are assigned to different classifications, but the assignments are subject to regular audits by regulatory agencies.

Once loans are assigned to rating classes, banks typically use historical chargeoff patterns to calculate a loan loss reserve for each class following SFAS 5 (FASB 1975, codified as ASC 450-10) guidance that losses are recognized when it is probable that future events will confirm the losses as of the balance sheet date. This focus only on credit losses that are estimated to have already occurred is commonly referred to as an "incurred loss" approach. Critics contend this approach ignores future expected losses that have not been incurred as of the balance sheet date (Trott 2009). SFAS 114 (FASB 1993, now codified in ASC 310) requires banks to supplement the loan loss reserve as calculated from the different loan-rating classes with additional specific reserves for particular loans, such as restructured loans.

Fair Value of Loans

Under SFAS 107 banks are required to disclose the fair values of all financial instruments, including loans, in the footnotes to the financial statements. These figures are audited as part of the annual audit (Barth, Beaver, and Landsman 1996). While fair value accounting can take different

[1] Loans held for sale are reported at the lower of cost or fair value, but they comprise only 0.75 percent of net bank loans in our sample (untabulated).
[2] See http://www.fdic.gov/regulations/laws/rules/5000-4700.html for a more detailed description of this process.

forms, it is most commonly associated with "exit value," or the amount for which the holder could sell an asset. SFAS 157 (FASB 2006), effective January 1, 2008 for most banks, codified exit values as the FASB's preferred interpretation of fair value for SFAS 107 disclosures. However, many loans are not actively traded and do not have a secondary market price, so banks frequently model the value of loans using discounted cash flows. Banks that use a discounted cash flow model to estimate the fair value of their loans use the current market interest rates for loans with similar properties, the interest rate they would use if they were making that same loan again currently (Tschirhart, O'Brien, Moise, and Yang 2007). Expected future cash flows are then discounted back to the present using the current market rate.

Theoretically, fair values from a discounted cash flow model can differ from net historical costs for three main reasons. First, since fair values consider *all* expected credit losses while loan loss reserves tend to focus only on *incurred* credit losses, the expected cash flows used to form the two measurements differ. Second, loan fair values change and can shift away from historical costs when the discount rate or market risk premium tied to the credit quality of banks' loans changes. Third, loan fair values can change when market-wide interest rates unrelated to credit quality change, for example due to changes in term structure or risk-free rates.[3]

In May 2010, the FASB proposed a significant change in reporting of loans and other financial instruments that would require banks to report both historical cost and fair value on the balance sheet. Under the proposal, banks would report gross loans and a loan loss reserve consistent with current U.S. GAAP, with changes in the loan loss reserve flowing through income. However, banks would additionally report a fair value adjustment line on the balance sheet used in calculating net loans. Changes in the fair value adjustment to loans would flow through other comprehensive income (FASB 2011). The FASB subsequently backed off the requirement to recognize loan fair values in the financial statements due to strong opposition predominantly by banking constituents (Cohn 2011; Moore 2011). However, as of this writing, the FASB has issued a new proposal that would once again require dual presentation of historical costs and fair values on the balance sheet, but would no longer recognize changes in the fair value through other comprehensive income (FASB 2013b).

Prior Literature

Much of the literature related to our study has explored the relation between stock prices and the allowance for loan losses, supplementary loan disclosures, and loan fair values. Subsequent to the issuance of SFAS 107, many academics began to focus on the required fair value disclosures and whether such disclosures are value-relevant to shareholders, incremental to existing recognized and disclosed loan information. Eccher, Ramesh, and Thiagarajan (1996) find that fair values are incrementally value-relevant over historical cost for securities but that *loan* fair values do not have incremental explanatory power. Nelson (1996) finds that fair values have no incremental explanatory power for securities or loans when controlling for future profitability. On the other hand, Barth et al. (1996) find that loan fair values do provide incremental explanatory power with respect to equity market values. Overall, however, the empirical evidence as to whether loan fair value information is value-relevant to shareholders is mixed.[4]

[3] Loan fair values in theory may also include an estimated price discount due to market illiquidity, which can also drive these values away from net historical costs. However, as Weil (2010) notes, in practice it appears that banks typically do not adjust loan fair values from discounted cash flow models for market illiquidity. Our discussions with bankers and auditors on this point are consistent with Weil's (2010) assertions.

[4] In contrast, a number of studies find that fair values of investment securities are incrementally associated with share prices. See Ryan (2007, 140) for a discussion.

In a recent study, Blankespoor, Linsmeier, Petroni, and Shakespeare (2013) find that leverage ratios based upon the fair value of *all* financial instruments, including loans, are more closely associated with credit spreads in the bond market than leverage ratios based upon historical cost values. This evidence implies that financial instruments, including loans, more directly reflect market perceptions of the overall credit risk of the bank when measured at fair value rather than at historical cost. Blankespoor et al. (2013) also find that leverage ratios based upon fair values for all financial instruments better predict bank failures than comparable leverage ratios based upon GAAP figures. Our study is different from Blankespoor et al. (2013) because we focus on reported loan fair values and examine realized credit losses tied to loans, such as chargeoffs and non-performing loans. From a financial statement user standpoint, predicting future defaults and non-performance of loan portfolios is critical because these fundamentals are a direct manifestation of the credit risk banks seek to manage. Thus, while evidence as to whether reported loan fair values correlate with equity or debt market prices is informative, *direct* evidence linking loan fair values to lending fundamentals is important as well.

Our study is similar in spirit to Evans, Hodder, and Hopkins (2013), who are among the first to examine how fair value information maps into the fundamentals of future firm performance. They focus on investment securities and find that fair value information for these assets does predict future fundamentals, such as realized income from securities. Our findings likely differ from Evans et al. (2013) because we examine loan credit losses, not securities income. Further, many investment securities are traded in functioning markets, while bank loans not held for sale generally are not. Thus, as we discuss further in the next section, fair value estimates for bank loans are potentially less relevant and reliable than fair values for other financial instruments.[5]

III. FAIR VALUE VERSUS HISTORICAL COST FOR BANK LOANS

Theory that Fair Value is Better in Predicting Credit Losses

Supporters of recognizing fair values for loans and other financial instruments consider fair value to be the most useful measurement attribute for understanding credit risk (FASB 2010, BC 57). The argument is that fair values are based in theory upon market prices or other market inputs, and market participants will pay more for cash flows with a lower credit risk. Thus, loan fair values will aggregate more information, particularly more forward-looking information, about potential credit losses than net historical costs. For example, Edward Trott, a former FASB member, contends that fair value is the most useful attribute for reporting loans and other debt instruments after acquisition because "fair value reflects the market's current estimate of future cash flows to be collected" (Trott 2009, 460). Trott (2009, 463–464) also argues that net historical loan costs do not provide users with information about loan collectability and credit losses because of the backward-looking nature of the loan loss reserve discussed in Section II.

Thomas Linsmeier, a current FASB member, makes a similar argument that fair values provide more useful information about impending credit losses:

[5] Our study is also similar to Chee (2011) who, in part of her study, examines the ability of loan fair values to predict future chargeoffs. She concludes that loan fair values have some limited incremental information content relative to historical cost information. Our study is different from Chee's (2011) because she examines the relation between aggregate loan fair values and price indices of mortgage-backed securities, as well as managerial incentives to overstate fair values and historical costs. We adopt a financial statement user perspective and focus exclusively on whether net historical cost or fair value better predicts credit losses at the bank level. Accordingly, our credit loss tests are different and more extensive as we examine a variety of variables tied to credit losses (chargeoffs, non-performing loans, and bank failures).

> fair value information provides early warnings to investors and regulators of changes in current market expectations when asset prices are declining and risk levels for financial institutions are increasing. Historic cost accounting with impairment estimates provides insufficient warning of these changes. (Linsmeier 2011, 2)

Aside from standard-setters, a recent policy paper by the International Monetary Fund on fair value accounting in the banking industry puts forward a similar argument (Novoa et al. 2009). This notion has been discussed in academic studies such as Bernard, Merton, and Palepu (1995) and Eccher et al. (1996), as well as in a Governmental Accountability Office (GAO 1991) review on failed banks during the Savings and Loan crisis. The GAO advocated the use of market values for problem loans to prevent banks from using their latitude in determining loan-carrying values to delay loss recognition.[6] Overall, if supporters of fair value for loans are correct, loan fair values should be a better predictor of future credit losses than net historical costs.

Theory that Fair Value is Worse in Predicting Credit Losses

Despite the preceding support, fair value accounting for loans and other financial instruments held for investment has many critics, particularly bank practitioners, as represented by the ABA, as well as several bank regulators.[7] A major concern with fair values for financial instruments centers on reliability (FASB 2007). This concern is particularly acute for loans because active markets for these assets do not exist in many cases. Thus, as discussed above, most loan fair values are based on discounted cash flow models using estimates of expected cash flows and current market interest rates for loans of similar maturity, terms, credit risk, and other factors, rather than on quoted market prices. This estimation process may introduce significant measurement error or bias into loan fair values, which threatens their ability to help predict future credit losses (Weil 2009). In addition, just as managers have the ability to manage the loan loss reserve due to its subjective nature, they also have the ability to manipulate loan fair values (Nissim 2003).

Critics also assert that loan fair values are not a relevant measurement attribute because the vast majority of loans are held for collection and are not sold, even if borrowers experience financial difficulty. If loans mature and all cash is collected, critics contend any changes in fair value reverse over the life of the loan and add unnecessary volatility to the measurement of performance and risk (ABA 2010). However, we note that if there are credit losses in the loan portfolio, this point is moot. Thus, the notion that fair values lack relevance applies only to the extent that all loans mature and all cash is collected.

A practical problem with loan fair values from a user perspective is that the fair values are disclosed only in the notes and not in the financial statements. As a result, managers may have less incentive to carefully estimate loan fair values and auditors may tolerate more measurement error in

[6] Supporters also tout other benefits of loan fair values relative to historical costs, such as more useful depictions of interest rate risk. Interest rate risk for banks is the risk that changes in interest rates, usually increases in interest rates, will cause adverse changes in current wealth and future interest margins due to duration mismatches. While examining the benefits of loan fair values in depicting interest rate risk is beyond the scope of this study, our robustness tests do examine the extent to which shifts in market-wide interest rates unrelated to credit risk affect the predictive ability of loan fair values. Fair values also potentially provide information about liquidity risk, which is the risk that the proceeds from the sale of assets are adversely affected by lack of market liquidity. However, as we discussed earlier, banks typically do not include liquidity adjustments in their calculation of loan fair values.

[7] In a recent letter to the FASB, the heads of the Board of Governors of the Federal Reserve System, the Federal Deposit Insurance Corporation, the National Credit Union Administration, the Office of the Comptroller of the Currency, and the Office of Thrift Supervision (2010) expressed their belief that fair value accounting is not appropriate for financial assets held for collection, such as loans.

these figures compared to recognized measurements (Libby, Nelson, and Hunton 2006). Loan fair values therefore might not be as useful for predicting credit losses due to a lack of effort toward measurement precision on the part of management. At the same time, some fair values may be reliable and useful, as illustrated by the findings in Barth (1994) that disclosed fair values of securities appear to be value-relevant to equity investors.

Overall, to the extent that loan fair value numbers are noisy and unreliable, loans stated at net historical cost should better predict future credit losses. Ultimately, the predictive ability of reported loan fair values versus net historical costs is an empirical question, which we explore in the next section.

IV. RESEARCH DESIGN AND EMPIRICAL RESULTS

Sample

We obtain the data for our empirical tests from the SNL Financial Institutions database, which includes regulatory data for all financial institutions required to file with the Federal Reserve and financial statement data from SEC filings. SNL maintains SFAS 107 loan fair value information beginning in 2005, so we use all available observations over the period 2005 to 2009. In total, we have 5,112 observations with SFAS 107 information for this period. However, our main empirical tests require the prediction of one-year-ahead credit losses, so we exclude 2009 fair values. Thus, our main empirical tests have 3,801 firm-year observations, for which we use fair values from 2005 to 2008 to predict credit losses from 2006 to 2009. Our sample consists of 1,174 unique commercial banks and thrifts ("banks").[8] Our sample captures a broad cross-section of banks in the U.S. because 583 of these banks currently trade on a major exchange, 353 trade on the OTCBB market, 177 trade in the "Pink Sheets," and 61 are private firms (untabulated).

Research Design

We focus on three independent variables in our empirical analysis, all of which are scaled by the value of gross loans to control for scale.[9] The first is the net historical cost of loans (*LOANHC*), which equals the gross principal balance of loans less the loan loss reserve, or equivalently, 1 minus the loan loss reserve as a percent of gross loans. Lower *LOANHC* therefore implies a higher loan loss reserve, which suggests higher expected credit losses. The second variable is the fair value of loans (*LOANFV*) per SFAS 107 disclosures. Lower *LOANFV ceteris paribus* implies a lower market price, which suggests higher market expectations of credit losses. The third is the difference between reported loan fair values and net historical costs (*FVDIFF*), which equals *LOANFV* – *LOANHC*.

We use two direct proxies for credit losses in our main analysis. The first is net chargeoffs (*CO*), which represents the amount of loans written off as uncollectible in a year, net of any recoveries. Chargeoffs represent recognition in the bank's financial statements that loan payments will not be collected. There is some discretion in recognizing chargeoffs, so we also use a second, less discretionary proxy for credit losses, non-performing loans (*NPL*) (Liu, Ryan, and Wahlen 1997). *NPL*s are loans that have been modified in a troubled debt restructuring, are past due, or for which interest revenue is not currently being recorded. *NPL*s essentially represent economic losses

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[8] Over 70 percent of the firms in our sample are legally structured as bank holding companies. While a bank holding company may consolidate multiple commercial banks, we include only the top level that reports regulatory information to the SEC.

[9] Inferences are similar if we use total assets as our scaling variable.

and forgone interest revenue related to poor credit quality of the borrower, so we refer to them as "credit losses" to simplify exposition. Both *CO* and *NPL* are scaled by gross loans.

We first conduct horse race tests in which we compare the ability of *LOANHC* and *LOANFV* to explain chargeoffs (*CO*) and *NPL*. We estimate the following OLS regressions on a pooled OLS basis (firm subscripts are omitted):

$$CO_{t+1} = \alpha + \beta_1 CO_t + \beta_2 NPL_t + \beta_3 LOANHC_t + \varepsilon_t; \quad (1)$$

$$CO_{t+1} = \alpha + \beta_1 CO_t + \beta_2 NPL_t + \beta_3 LOANFV_t + \varepsilon_t; \quad (2)$$

$$NPL_{t+1} = \alpha + \beta_1 NPL_t + \beta_2 LOANHC_t + \varepsilon_t; \quad (3)$$

$$NPL_{t+1} = \alpha + \beta_1 NPL_t + \beta_2 LOANFV_t + \varepsilon_t. \quad (4)$$

We model future chargeoffs in Equations (1) and (2) as a function of current chargeoffs and non-performing loans, consistent with prior work, such as Wahlen (1994). If *LOANHC* and *LOANFV* help to predict credit losses, then we expect them to be negatively associated with future chargeoffs because lower carrying values imply larger credit impairments and higher future defaults. If loans stated on a net historical cost basis better predict chargeoffs, we expect the explanatory power (R^2) of Equation (1) to dominate Equation (2), and *vice versa*. We follow Dechow (1994) and test the explanatory power of each model using the Vuong (1989) test.

For Equations (3) and (4), we model future non-performing loans as a function of past non-performing loans, because we expect loan credit quality to be sticky across firms over time. Current charge-offs (CO_t) are included in Equations (1) and (2) but omitted from Equations (3) and (4) because loans should first become non-performing or past due and then subsequently be charged-off when they are deemed uncollectible. Consequently, *NPL*s should lead *CO*s (Liu and Ryan 1995). If *LOANHC* and *LOANFV* help to predict credit losses, then we expect them to be negatively associated with future *NPL*s. For completeness, we also estimate a changes specification using first differences for Equations (1) through (4).

Evaluating the predictive ability of *LOANHC* and *LOANFV* in the context of other available variables as in Equations (1) through (4) is consistent with a user perspective. However, these models could be problematic in testing the two competing theories discussed earlier. Since *CO*s and *NPL*s tend to be sticky across firms and over time, current *CO* and *NPL* will account for much of the predictive ability in these models, leaving less room for *LOANHC* and *LOANFV* to demonstrate their predictive ability on a standalone basis. In fact, all of the models above could offer relatively good predictions even if *LOANHC* or *LOANFV* themselves have little predictive ability simply because these models include current *CO* and current *NPL*. Consequently, we also estimate simplified models that contain only the variables of interest to isolate the predictive ability of *LOANHC* versus *LOANFV*. We weigh the evidence across both models when evaluating the predictive ability of reported loan fair values versus net historical costs.

Even if one variable is a better predictor in an absolute sense, the other variable may still offer some incremental predictive ability. Thus, we also test the incremental predictive ability of reported loan fair values by estimating the following equations:

$$CO_{t+1} = \alpha + \beta_1 CO_t + \beta_2 NPL_t + \beta_3 LOANHC_t + \beta_4 FVDIFF_t + \varepsilon_t; \quad (5)$$

$$NPL_{t+1} = \alpha + \beta_1 NPL_t + \beta_2 LOANHC_t + \beta_3 FVDIFF_t + \varepsilon_t. \quad (6)$$

If loan fair value information is incrementally useful in predicting future credit losses, then we expect the coefficient on *FVDIFF*, defined as $LOANFV - LOANHC$, to be negative and significant. More positive values of *FVDIFF* mean that fair values are above carrying values on a historical costs basis. Thus, positive (negative) values of *FVDIFF* should be associated with lower (higher) future credit losses, assuming fair value differences pick up credit quality differences.

We also examine the predictive ability of reported loan fair values and historical costs for bank failures, which are extreme outcomes tied to credit loss fundamentals. Bank failures surged during the recent financial crisis, and the SEC (2008) concluded in a recent study that poor lending practices and the accompanying credit losses in loan portfolios were the driving forces behind bank failures. Our main bank failure model follows prior banking literature based on Thomson (1991). Specifically, we estimate the following logistic regression:

$$\begin{aligned}\Pr(FAILn,\ \text{where } n = 1,2,3)_t = \alpha &+ \beta_1 EQUITYCAP_t + \beta_2 LOAN\%_t + \beta_3 NPL_t \\ &+ \beta_4 LIQUIDITY_t + \beta_5 ROA_t + \beta_6 SIZE_t + \beta_7 HOLDINGCO_t \\ &+ \beta_8 DEPOSIT_t + \beta_9 LOANHC_t + \beta_{10} FVDIFF_t + \varepsilon_t.\end{aligned} \tag{7}$$

FAIL1 (*FAIL2*) [*FAIL3*] for year *t* is an indicator variable equal to 1 if a bank fails within one year (two years) [three years] after the availability of annual accounting data in year *t*, which we assume is three months after year-end. Defining the dependent variable this way affords us flexibility in expanding the prediction window for future failure. Because R^2 is not well defined for a logistic regression, we use an incremental prediction model and test the association of *FVDIFF* with the probability of bank failure. Other variables in Equation (7) are prominent in the bank failure literature and we define them in the notes for the tables that follow.

Credit Loss Prediction Tests

Table 1 contains descriptive statistics for variables used in our credit loss prediction tests. We also include descriptives for other variables to highlight important features of our sample. To reduce the influence of outliers, all variables are winsorized at the extreme 1 percent of their distribution.[10] *LOAN%* indicates that net loans (gross loans less loan loss reserves [LLR]) account for about 70 percent of all assets on average in our sample. By comparison, *SEC%* indicates that investment securities, which have been the focus of more scholarly work on fair value accounting and intense controversy during the financial crisis, account for only about 18 percent of assets.

Turning to the variables in our main tests, net chargeoffs (*CO*) are about 0.50 percent of gross loans on average per year, while *NPL*s are about 1.8 percent of gross loans. The mean *LOANHC* is 98.6 percent of gross loans, which implies a loan loss reserve of 1.4 percent. The mean *LOANFV*, at 98.8 percent of gross loans, is slightly higher than *LOANHC* over our sample period, but the medians are virtually identical. Thus, despite the recent heated debate over loan fair values, reporting loans at fair value would not impact banks' balance sheets to a large extent, on average. However, we point out that *LOANFV* has nearly three times the standard deviation of *LOANHC*, consistent with loan fair values being more volatile and dispersed in the cross-section.

Table 2 presents correlations between the variables in our main tests. We discuss the above diagonal Pearson correlations for convenience. Not surprisingly, net chargeoffs (*CO*) are positively correlated with *NPL*s ($r = 0.55$, $p < 0.01$). Net historical costs (*LOANHC*) and reported loan fair values (*LOANFV*) are positively correlated, but only at $r = 0.25$ ($p < 0.01$). On a univariate basis, both future *CO* ($r = -0.57$, $p < 0.01$) and *NPL* ($r = -0.43$, $p < 0.01$) are more highly correlated with *LOANHC* than *LOANFV* (-0.12, $p < 0.01$; -0.02, $p = 0.18$). Thus, net historical cost values appear to be more strongly related to future credit losses than reported loan fair values on a univariate basis.

[10] Our results are similar regardless of whether we trim outliers or do not adjust for them.

TABLE 1

Descriptive Statistics

Variable	Mean	Q1	Median	Q3	Std. Dev.
LOAN%	0.70195	0.63786	0.71663	0.78356	0.11762
SEC%	0.18495	0.10491	0.16677	0.24345	0.11340
RE%	0.78726	0.72260	0.80920	0.88460	0.14597
MKTCAP	0.62989	0.02583	0.06053	0.19434	2.67847
CO	0.00495	0.00045	0.00155	0.00455	0.00908
NPL	0.01754	0.00283	0.00790	0.02109	0.02473
LOANHC	0.98632	0.98460	0.98789	0.99017	0.00709
LOANFV	0.98789	0.97882	0.98782	0.99798	0.02356
FVDIFF	0.00162	(0.00692)	0.00056	0.01014	0.02154

The full sample includes 5,112 firm-year observations, averaging 1,022 banks per year, for the years 2005–2009. This table reports descriptive statistics over the entire sample period. To minimize the influence of outliers, all variables are winsorized at the 1 percent and 99 percent levels. Variable definitions are as follows (firm and year subscripts are omitted).

Variable Definitions:
LOAN% = total book value of net loans divided by total book value of assets at the end of year *t*;
SEC% = total book value of securities divided by total book value of assets at the end of year *t*. Total securities include trading securities, available-for-sale securities, held-to-maturity securities, and other securities. Note: Trading securities and available-for-sale securities are reported at fair value; held-to-maturity securities and other securities are reported at amortized cost;
RE% = total book value of real estate loans (both consumer and commercial) divided by total book value of loans at the end of year *t*;
MKTCAP = total market capitalization, in billions, at the end of year *t*. Calculated as total common shares outstanding multiplied by stock price at the end of the year;
CO = total chargeoffs net of recoveries divided by gross loans at the end of year *t*;
NPL = total non-performing loans divided by gross loans at the end of year *t*. Non-performing loans are loans for which the interest is no longer accruing or the terms have been renegotiated;
LOANHC = net loans per the balance sheet, equal to gross loans less the loan loss reserve, divided by gross loans at the end of year *t*;
LOANFV = fair value of loans per SFAS 107 disclosure divided by gross loans at the end of year *t*; and
FVDIFF = total fair value of loans per SFAS 107 disclosure minus total carrying (book) value of loans, divided by gross loans at the end of year *t*.

Table 3 reports our main test results with standard errors clustered by firm.[11] Panel A contains our horse race tests for net chargeoffs. The R^2 for Equation (1) is 0.528 versus 0.485 for Equation (2), and this difference in significant ($p < 0.01$). Thus, the model with the net historical costs (*LOANHC*) outperforms the model with the reported loan fair values (*LOANFV*) in predicting net chargeoffs. The estimated coefficient estimate on *LOANHC*, –0.522, is almost 25 times the estimated coefficient on *LOANFV*, –0.021, and this difference is significant ($p < 0.01$, untabulated). Thus, on average, 52 percent of the loan loss reserve results in a next period chargeoff versus only 2 percent of the difference between gross loans and fair values. The standard deviation of *LOANFV* is roughly three times that of *LOANHC* but this difference alone is not

[11] Inferences in Table 3 regarding the relative size of individual coefficients are similar when we cluster standard errors by both firm and year (Petersen 2009). Clustering does not affect model fit statistics like R^2 or mean squared error, so we use the standard approach in Dechow (1994) without clustering to calculate Vuong (1989) statistics. We do not table standard errors clustered by year (or firm and year) because we have over 1,000 banks but only four years of cross-sectional data.

TABLE 2

Select Variable Correlations
Pearson (top) and Spearman (bottom) Correlations

Variable	CO_t	CO_{t+1}	NPL_t	NPL_{t+1}	$LOANHC_t$	$LOANFV_t$
CO_t		**0.59494**	**0.54787**	**0.4449**	**−0.51065**	**−0.13195**
CO_{t+1}	**0.6282**		**0.62662**	**0.70483**	**−0.57168**	**−0.1156**
NPL_t	**0.49482**	**0.57224**		**0.71446**	**−0.49796**	**−0.0622**
NPL_{t+1}	**0.41533**	**0.65655**	**0.68749**		**−0.42821**	−0.02195
$LOANHC_t$	**−0.37814**	**−0.44789**	**−0.33393**	**−0.29943**		**0.24791**
$LOANFV_t$	0.00764	**0.06526**	**0.04652**	**0.10789**	**0.21181**	

The sample for this table includes 3,801 firm-year observations for the years 2005–2008. 2009 *LOANHC* and *LOANFV* observations are excluded because we require credit loss variables to be available in year t+1. Data in bold are significant at the 0.01 level or better, two-tailed. To minimize the influence of outliers, all variables are winsorized at the 1 percent and 99 percent levels.
Variables are as defined in Table 1.

enough to account for such a large difference in coefficients. Instead, the lower predictive power of Equation (2) suggests that *LOANFV* contains more measurement error and noise with respect to credit quality compared to *LOANHC*, which likely results in the smaller estimated coefficient on *LOANFV*.

The results in Table 3, Panel A also suggest that the relatively poor predictive ability of *LOANFV* appears to be compensated by higher weights in Equation (2) on CO_t and NPL_t, both of which have strong predictive ability for CO_{t+1}. Table 3, Panel A also reports estimates from the simplified models in (1a) and (2a) that contain only *LOANHC* and *LOANFV*. The explanatory power of Model (1a) with only *LOANHC* dominates Model (2a) with only *LOANFV* by a wide margin reflected in an R^2 of 0.327 versus 0.013, $p < 0.01$.

Panel B of Table 3 reports results comparing the prediction of *NPL*s. Model (3) with *LOANHC* outperforms Model (4) with *LOANFV* ($p = 0.026$), although the difference in R^2 is not large in an economic sense (0.517 versus 0.511). To explore whether this small difference is attributable to the relatively strong predicative ability of NPL_t, we also report estimates from the simplified models in Equations (3a) and (4a) that do not contain NPL_t. Model (3a) outperforms Model (4a) by a wide margin with an R^2 of 0.1832 versus 0.0002, $p < 0.01$. As in Panel A, the coefficient on *LOANHC* is larger than the coefficient on *LOANFV*, both economically and statistically ($p < 0.01$, untabulated). We also note that the coefficient on *LOANFV* in Model (4) is only marginally significant and has an unexpected sign.

In Panel C of Table 3, we repeat our estimation of Equations (1) through (4) using a changes specification in which all variables have been first-differenced. Inferences from these specifications are similar to the levels specifications in Panels A and B in which net historical costs predict credit losses better than reported loan fair values. Table 3, Panels D and E contain estimates of Equations (5) and (6), which test the incremental explanatory power of differences between reported loan fair values and historical costs. In Panel D, which predicts future chargeoffs, the coefficient estimate on *FVDIFF* is 0.003, which is not significantly different from 0. Thus, differences between reported loan fair values and historical costs have no incremental predictive ability for future chargeoffs. In Panel E, which predicts future *NPL*s, the coefficient estimate on *FVDIFF* is 0.064 ($p < 0.01$). However, the sign of this coefficient is inconsistent with economic intuition in that higher fair values predict greater future *NPL*s.

TABLE 3

Ability of Loans at Historical Cost and Fair Value to Predict Future Chargeoffs and Non-Performing Loans In Sample

Panel A: Ability of Loans at Historical Cost and Fair Value to Explain Net Chargeoffs

$$CO_{t+1} = \alpha + \beta_1 CO_t + \beta_2 NPL_t + \beta_3 LOANHC_t + \varepsilon_t. \quad (1)$$
$$CO_{t+1} = \alpha + \beta_1 CO_t + \beta_2 NPL_t + \beta_3 LOANFV_t + \varepsilon_t. \quad (2)$$

	Model (1)		**Model (2)**		**Model (1a)**		**Model (2a)**	
	Coeff.	**t-stat**	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**
α_0 Intercept	0.517	10.83***	0.022	3.01***	1.142	22.44***	0.064	5.00***
β_1 CO_t	0.529	8.21***	0.690	10.74***				
β_2 NPL_t	0.233	12.21***	0.287	14.29***				
β_3 $LOANHC_t/LOANFV_t$	(0.522)	−10.82***	(0.021)	−2.89***	(1.150)	−22.36***	(0.058)	−4.55***
	Adj. R^2	0.5279	Adj. R^2	0.4845	Adj. R^2	0.3266	Adj. R^2	0.0131
	Z-stat	6.34***			Z-stat	13.53***		

Panel B: Ability of Loans at Historical Cost and Fair Value to Explain Non-Performing Loans

$$NPL_{t+1} = \alpha + \beta_1 NPL_t + \beta_2 LOANHC_t + \varepsilon_t. \quad (3)$$
$$NPL_{t+1} = \alpha + \beta_1 NPL_t + \beta_2 LOANFV_t + \varepsilon_t. \quad (4)$$

	Model (3)		**Model (4)**		**Model (3a)**		**Model (4a)**	
	Coeff.	**t-stat**	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**
α_0 Intercept	0.517	5.61***	(0.023)	−1.34	2.285	15.86***	0.050	1.77*
β_1 NPL_t	1.183	30.16***	1.270	35.88***				
β_2 $LOANHC_t/LOANFV_t$	(0.516)	−5.54***	0.030	1.75*	(2.292)	−15.74***	(0.030)	−1.03
	Adj. R^2	0.5172	Adj. R^2	0.5107	Adj. R^2	0.1832	Adj. R^2	0.0002
	Z-stat	2.23**			Z-stat	9.76***		

(continued on next page)

To summarize, our horse race tests in Table 3 indicate that net historical loan costs are a better predictor of future credit losses relative to reported loan fair values. Likewise, our test of incremental prediction finds that differences between reported loan fair values and net carrying values for book purposes do not convey meaningful information about future credit losses beyond the information in net historical costs.

Do the Results Hold on an Out of Sample Basis?

Because we are concerned with prediction from the standpoint of a financial statement user, we next make an out-of-sample comparison by using data from all years prior to year *t* to predict credit losses in the following year. Using parameters from this model along with covariate values from year *t*, we then form a prediction of credit losses in year *t*+1 and calculate the absolute value of the prediction error. For example, we use 2005 annual data to predict credit losses in 2006 using both the historic cost and fair value models and then use the parameters from each model to predict credit losses in 2007 using 2006 covariate annual data. To minimize the influence of outliers, we winsorize prediction errors at the extreme 1 percent of the distribution. Table 4 contains the mean absolute forecast errors for Models (1) through (4) on an out-of-sample basis. Because the same

TABLE 3 (continued)

Panel C: Changes Specifications

$$\Delta CO_{t+1} = \alpha + \beta_1 \Delta CO_t + \beta_2 \Delta NPL_t + \beta_3 \Delta LOANHC_t + \varepsilon_t. \quad (\Delta 1)$$
$$\Delta CO_{t+1} = \alpha + \beta_1 \Delta CO_t + \beta_2 \Delta NPL_t + \beta_3 \Delta LOANFV_t + \varepsilon_t. \quad (\Delta 2)$$
$$\Delta NPL_{t+1} = \alpha + \beta_1 \Delta NPL_t + \beta_2 \Delta LOANHC_t + \varepsilon_t. \quad (\Delta 3)$$
$$\Delta NPL_{t+1} = \alpha + \beta_1 \Delta NPL_t + \beta_2 \Delta LOANFV_t + \varepsilon_t. \quad (\Delta 4)$$

	Model (Δ1)		Model (Δ2)		Model (Δ3)		Model (Δ4)	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Intercept	0.003	18.72***	0.003	17.04***	0.010	27.23***	0.011	25.66***
ΔCO_t	(0.153)	−2.36**	(0.040)	−0.63				
ΔNPL_t	0.207	8.24***	0.335	14.14***	0.231	3.46***	0.439	7.74***
$\Delta LOANHC_t/\Delta LOANFV_t$	(1.006)	−11.39***	(0.047)	−5.17***	(1.436)	−7.10***	(0.064)	−2.83***
	Adj. R^2	0.3616	Adj. R^2	0.2668	Adj. R^2	0.1244	Adj. R^2	0.0869
	Z-stat	5.13***			Z-stat	3.33***		

Panel D: Incremental Ability of Fair Value Difference to Explain Net Chargeoffs

$$CO_{t+1} = \alpha + \beta_1 CO_t + \beta_2 NPL_t + \beta_3 LOANHC_t + \beta_4 FVDIFF_t + \varepsilon_t. \quad (5)$$

	Model (5)	
	Coeff.	t-stat
Intercept	0.518	10.84***
CO_t	0.530	8.19***
NPL_t	0.232	12.16***
$LOANHC_t$	(0.522)	−10.83***
$FVDIFF_t$	0.003	0.47
Adj. R^2		0.5278

(continued on next page)

sample of firm-years is used to generate forecast errors across models, the forecast errors are not independent across equations. Consequently, we use paired t-tests, with pairing at the firm-year level, when testing for average differences in forecast errors across equations.

Results for net chargeoffs in Table 4, Panel A show that the average absolute forecast error for Model (1) with *LOANHC* is 0.0028 compared to 0.0029 for Model (2) with *LOANFV*. This difference is equal to roughly 2 percent (6 percent) of the mean (median) realized charge-off in the sample and is significant at conventional levels ($t = -7.86$, $p < 0.01$). It is important to note that neither model fares very well out of sample, in the sense that the average magnitude of the forecast error is roughly equal to 50 percent of the average sample net chargeoff as shown in Table 1.[12]

Comparison of the average forecast errors across Models (1) and (2) to gauge the predictive ability of *LOANHC* and *LOANFV* is somewhat misleading because much of the predictive ability of these models is attributable to CO_t and NPL_t. For this reason, we also report forecast errors using the simplified models in Models (1a) and (2a) with only *LOANHC* and *LOANFV*. On this basis, net

[12] The fact that the out-of-sample results are weaker than the in-sample results is a common econometric issue. Inoue and Kilian (2000) demonstrate that out-of-sample tests are less powerful than in-sample tests and caution researchers to not assume that out-of-sample weakness implies that in-sample results are spurious.

TABLE 3 (continued)

Panel E: Incremental Ability of Fair Value Difference to Explain Non-Performing Loans

$$NPL_{t+1} = \alpha + \beta_1 NPL_t + \beta_2 LOANHC_t + \beta_3 FVDIFF_t + \varepsilon_t. \quad (6)$$

	Model (6)	
	Coeff.	**t-stat**
Intercept	0.527	5.70***
NPL_t	1.176	30.01***
$LOANHC_t$	(0.526)	−5.63***
$FVDIFF_t$	0.064	3.71***
Adj. R^2		0.5191

*, **, *** Indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively.
The primary sample for this table includes 3,801 firm-year observations for the years 2005–2008. Panel A follows Dechow (1994) and runs a "horse race" between $LOANHC_t$ and $LOANFV_t$ in their ability to explain CO_{t+1}. Vuong's (1989) Z-statistic tests the null hypothesis that the *LOANHC* model (Model (1)) and *LOANFV* model (Model (2)) are equally close in their ability to explain CO_{t+1}. A positive number indicates that $LOANHC_t$ is better at predicting CO_{t+1}; a negative number indicates that $LOANFV_t$ is better at predicting CO_{t+1}. Model (1a) and Model (2a) are simplified versions of Model (1) and Model (2), respectively. Similar to Panel A, Panel B runs a horse race between $LOANHC_t$, and $LOANFV_t$ in their ability to explain NPL_{t+1}. Vuong's Z-statistic tests the null hypothesis that the *LOANHC* model (Model (3)) and *LOANFV* model (Model (4)) are equally close in their ability to explain NPL_{t+1}. Model (3a) and Model (4a) are simplified versions of Model (3) and Model (4), respectively. Panel C repeats estimations of Equations (1) through (4) using a changes specification, which reduces the available sample to 2,614 observations. Panel D tests the incremental ability of $FVDIFF_t$ to explain CO_{t+1} given CO_t, NPL_t, and $LOANHC_t$. Similar to Panel D, Panel E tests the incremental ability of $FVDIFF_t$ to explain NPL_{t+1} given NPL_t and $LOANHC_t$. To minimize the influence of outliers, all variables are winsorized at the 1 percent and 99 percent levels. t-statistics are based on standard errors that have been adjusted for clustering by firm.
Variables are as defined in Table 1.

historical costs outperform reported loan fair values by a wider margin. The average unsigned forecast error of 0.0039 for Model (2) is greater than the forecast error of 0.0035 for Model (1), and this difference is statistically significant ($p < 0.01$).

Table 4, Panel B presents mean unsigned forecast errors for predicting *NPL*s. For the full models, the model using *LOANHC* has a slightly smaller forecast error (0.00893) than the model using *LOANFV* (0.00895), but this difference is small and is marginally insignificant ($t = -1.44$, $p = 0.15$). For simplified models that isolate *LOANHV* versus *LOANFV*, however, the mean forecast error using *LOANFV* (0.0124) is significantly larger than the forecast error using *LOANHC* (0.0118) ($t = -13.06$, $p < 0.01$). In Panel C of Table 4, we repeat the out-of-sample tests using changes specifications. For both charge-offs and non-performing loans, the models using net historical costs outperform the models using reported loan fair values. In summary, on an out-of-sample basis, net historical costs tend to produce more accurate predictions of future credit losses.

Do Changes in Market-Wide Interest Rates Handicap Loan Fair Values?

As discussed in Section II, loan fair values change when market interest rates for similar loans change. To the extent that changes in interest rates reflect, for example, a drop in economy-wide interest rates due to monetary policy rather than a change in credit risk, the differences between loan fair values and net historical costs may not be indicative of differences in underlying credit risk, which would limit the ability of loan fair values to predict future credit losses. Under current GAAP, banks do not separately report the effect of changes in non-credit-related discount rates on loan fair values. Therefore, to address this issue, we regress *LOANFV* on a pooled basis on the risk-free rate, proxied by the ten-year Treasury bond rate, each fiscal year-end over our sample period,

TABLE 4

Ability of Loans at Historical Cost and Fair Value to Predict Future Chargeoffs and Non-Performing Loans Out of Sample

Panel A: Ability of Loans at Historical Cost and Fair Value to Predict Net Chargeoffs Out of Sample

$$CO_{t+1} = \alpha + \beta_1 CO_t \beta_2 NPL_t + \beta_3 LOANHC_t + \varepsilon_t. \quad (1)$$
$$CO_{t+1} = \alpha + \beta_1 CO_t + \beta_2 NPL_t + \beta_3 LOANFV_t + \varepsilon_t. \quad (2)$$

	Model (1)	Model (2)	Model (1a)	Model (2a)
Mean FE	0.0028	0.0029	0.0035	0.0039
t-statistic (diff.)	−7.86***		−17.83***	

Panel B: Ability of Loans at Historical Cost and Fair Value to Predict Non-Performing Loans Out of Sample

$$NPL_{t+1} = \alpha + \beta_1 NPL_t + \beta_2 LOANHC_t + \varepsilon_t. \quad (3)$$
$$NPL_{t+1} = \alpha + \beta_1 NPL_t + \beta_2 LOANFV_t + \varepsilon_t. \quad (4)$$

	Model (3)	Model (4)	Model (3a)	Model (4a)
Mean FE	0.0089	0.0089	0.0118	0.0124
t-statistic (diff.)	−1.44		−13.06***	

Panel C: Changes Specifications

$$\Delta CO_{t+1} = \alpha + \beta_1 \Delta CO_t + \beta_2 \Delta NPL_t + \beta_3 \Delta LOANHC_t + \varepsilon_t. \quad (\Delta 1)$$
$$\Delta CO_{t+1} = \alpha + \beta_1 \Delta CO_t + \beta_2 \Delta NPL_t + \beta_3 \Delta LOANFV_t + \varepsilon_t. \quad (\Delta 2)$$
$$\Delta NPL_{t+1} = \alpha + \beta_1 \Delta NPL_t + \beta_2 \Delta LOANHC_t + \varepsilon_t. \quad (\Delta 3)$$
$$\Delta NPL_{t+1} = \alpha + \beta_1 \Delta NPL_t + \beta_2 \Delta LOANFV_t + \varepsilon_t. \quad (\Delta 4)$$

	Model (Δ1)	Model (Δ2)	Model (Δ3)	Model (Δ4)
Mean FE	0.0038	0.0040	0.0132	0.0134
t-statistic (diff.)	−6.20***		−5.00***	

*** Indicates significance at the 1 percent level.

The sample for this table includes 2,844 firm-year observations for the years 2006–2008. Using parameters estimated from Equations (1) through (4) in prior years, along with covariate values from year t, we then form a prediction of credit losses in year t+1, and calculate the absolute value of the mean forecast error. Panel A performs out-of-sample tests on the ability of $LOANHC_t$ and $LOANFV_t$ to predict CO_{t+1}. The simplified models use only the covariate value on $LOANHC_t$ and $LOANFV_t$ to predict CO_{t+1}. A negative t-statistic indicates that using $LOANFV_t$ results in a greater forecast error than using $LOANHC_t$ at predicting CO_{t+1}; a positive t-statistic indicates that using $LOANFV_t$ results in a smaller forecast error than using $LOANHC_t$ at predicting CO_{t+1}. Panel B performs out-of-sample tests on the ability of $LOANHC_t$ and $LOANFV_t$ to predict NPL_{t+1}. The simplified models use only the covariate value on $LOANHC_t$ and $LOANFV_t$ to predict NPL_{t+1}. Panel C repeats estimations of Equations (1) through (4) using a changes specification, which reduces the available sample to 2,614 observations. Due to correlations across equations, we use paired t-statistics with the pairing at the firm-year level. To minimize the influence of outliers, all variables are winsorized at the 1 percent and 99 percent levels.

Variables are as defined in Table 1.

and calculate residuals for this variable, which we label *LOANFVe*. This procedure attempts to remove the average effect of the change in interest rates unrelated to credit risk from fair values. We then repeat the horse race tests in Table 3 using *LOANFVe* with results for predicting chargeoffs presented in Panel A of Table 5. Overall, after controlling for risk-free interest rates over time, net historical costs still dominate reported loan fair values in predictive ability. Inferences involving the prediction of *NPL*s and our incremental tests are similar to those presented in Table 3, so we do not tabulate these specifications for brevity.[13]

Predicting Credit Losses Multiple Years into the Future

Our tests in Table 3 focus on one-year-ahead predictions of credit losses from 2005 to 2009. Since loan fair values theoretically consider *all* expected future credit losses, while net historical costs theoretically consider only *incurred* credit losses, it is possible that loan fair values outperform net historical costs in a prediction horizon beyond one year. To (1) predict credit losses over multiple future periods, and (2) assess the sensitivity of our findings to the sample period examined, we hand-collect all available SFAS 107 data from 1994 for 125 banks chosen at random from our main sample. This procedure yields a sample of 1,156 firm-year observations spanning the years 1994 to 2009.

Using this hand-collected sample, we re-perform the horse race tests in Table 3. Given the longer time-series in this sample and the volatility of loan fair values, we include year fixed effects to control for economic shocks, such as changes in risk-free interest rates common to all firms over time and focus on the prediction of future credit losses across firms. We also accumulate net chargeoffs over one-, two-, and three-year periods for prediction purposes.

Two patterns in the results for predicting chargeoffs in Panel B of Table 5 are worth noting.[14] First, for one-year horizons, the results using a sample that spans 1994 to 2008 as year *t* are similar to our main results in Table 3, suggesting that our main results are not driven by the time period we examine. Second, reported loan fair values do not predict credit losses more accurately when multiple future periods are considered. In fact, in all cases net historical loan values do a better job of predicting future chargeoffs up to three years in advance.[15]

Bank Failures

Table 6 contains our bank-failure-prediction tests. Overall, 75 banks from our sample fail sometime between 2005 and 2010, and we have sufficient data to conduct our tests for 73 of these banks.[16] Table 6, Panel A presents coefficient estimates from our main failure model in Equation (7). We tabulate results using *FAIL2*, which equals 1 if a bank fails within two years after year *t*'s

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[13] To further address the interest rate issue, we also sorted banks on the portion of their assets or net assets with interest rates that reset within one year, which captures the extent of variable rate versus fixed rate assets. Banks with relatively more (less) fixed rate assets will have loan fair values more (less) affected by swings in market-wide interest rates, since the cash flows for fixed-rate debt do not reset when market rates change. Thus, if some banks have more fixed-rate loans than others, then changes in interest rates unrelated to credit risk could lead to differences in loan fair values across banks unrelated to credit risk. If this phenomenon contributes materially to our results, then we expect to find differences in our prediction tests for banks with relatively high versus low holdings of variable-rate assets. However, we do not find a significant difference across these groups (untabulated).

[14] We tabulate chargeoffs for brevity. For *NPL*s in the hand-collected sample, we find no significant difference between Equations (3) and (4) in the full models, but we do find significantly greater explanatory power at all horizons in the simplified models for Equation (3a) using *LOANHC* versus Equation (4a) using *LOANFV*.

[15] When we include firm fixed effects in this regression, net historical costs continue to have better predictive ability one year ahead, but there are no significant differences two and three years ahead, as neither loan fair values nor historical costs are significantly related to future chargeoffs once across-firm differences in credit losses and loan values are neutralized via firm fixed effects.

[16] According to the FDIC, 325 banks failed from 2005 to 2010. However, after excluding private banks and wholly owned subsidiaries that do not report SFAS 107 disclosures, only 75 of the 325 banks remain.

TABLE 5

Effects of Market-Wide Interest Rates and Cumulating Credit Losses over Multiple Years

Panel A: Incremental Ability of Loans at Net Historical Cost and Fair Value Differences Adjusted for Changes in Risk-Free Rates to Predict Future Chargeoffs

$$CO_{t+1} = \alpha + \beta_1 CO_t + \beta_2 NPL_t + \beta_3 LOANHC_t + \varepsilon_t. \quad (1)$$
$$CO_{t+1} = \alpha + \beta_1 CO_t + \beta_2 NPL_t + \beta_3 LOANFVe_t + \varepsilon_t. \quad (2)$$

	Model (1)		Model (2)		Model (1a)		Model (2a)	
	Coeff.	**t-stat**	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**
α_0 Intercept	0.517	10.83***	0.001	6.39***	1.142	22.44***	0.006	32.86***
β_1 CO_t	0.529	8.21***	0.673	10.67***				
β_2 NPL_t	0.233	12.21***	0.284	14.23***				
β_3 $LOANHC_t/LOANFVe_t$	(0.522)	−10.82***	(0.040)	−5.15***	(1.150)	−22.36***	(0.110)	−8.09***
	Adj. R^2	0.5279	Adj. R^2	0.4885	Adj. R^2	0.3266	Adj. R^2	0.0464
	Z-stat	5.98***			Z-stat	12.93***		

Panel B: Ability of Historical Costs and Fair Values to Predict Future Chargeoffs—In Sample 1994 to 2009

$$CO_{t+x} = \alpha + \beta_1 CO_t + \beta_2 NPL_t + \beta_3 LOANHC_t + YRDummy + \varepsilon_t. \quad (1)$$
$$CO_{t+x} = \alpha + \beta_1 CO_t + \beta_2 NPL_t + \beta_3 LOANFV_t + YRDummy + \varepsilon_t. \quad (2)$$

		1 Year Ahead		2 Years Ahead		3 Years Ahead	
		Model (1) Coeff.	**Model (2) Coeff.**	**Model (1) Coeff.**	**Model (2) Coeff.**	**Model (1) Coeff.**	**Model (2) Coeff.**
α_0	Intercept	0.254***	0.027**	0.275**	0.035**	0.329**	0.041**
β_1	CO_t	0.519***	0.612***	0.967***	1.080***	1.205***	1.381***
β_2	NPL_t	0.111**	0.126**	0.040	0.055	0.002	0.026
β_3	$LOANHC_t/LOANFV_t$	(0.249)***	(0.019)*	(0.260)**	(0.017)	(0.314)**	(0.023)
	Adj. R^2	0.5227	0.5030	0.4105	0.3995	0.3138	0.3003
	n	1,008		881		764	
	Z-stat	2.7**		1.86*		1.78*	

(continued on next page)

accounting data are available, as the dependent variable. Inferences are similar when we use *FAIL3*, which captures a three-year failure window, as the dependent variable.[17] As expected, banks with more loans, more non-performing loans, more average branch deposits, and lower net historical loan values (*LOANHC*) are more likely to fail in the near future. The coefficient on *FVDIFF* is –0.60 and is insignificant ($p = 0.91$).[18]

[17] Very few (less than five) of the banks that fail do so within one year of the last year of available financial statements. Thus, *FAIL1* rarely equals 1 and we do not use this variable in our empirical tests. Most commonly, failed banks will report in year *t*, not report any financial statements for year *t*+1, and then fail sometime afterward.

[18] Inferences are similar if we use a hazard model to predict banks' survival time in days from the end of year *t* and are available upon request. Inferences are also unchanged if we include a traditional leverage ratio (liabilities to assets or equity) in Equation (7), as the effect of leverage is largely subsumed by *EQUITYCAP*, *LIQUIDITY*, and *DEPOSIT*.

TABLE 5 (continued)

Panel C: Ability of Historical Costs and Fair Values to Predict Future Chargeoffs (Simplified Models)—In Sample 1994 to 2009

	1 Year Ahead		2 Years Ahead		3 Years Ahead	
	Model (1a) Coeff.	Model (2a) Coeff.	Model (1a) Coeff.	Model (2a) Coeff.	Model (1a) Coeff.	Model (2a) Coeff.
α_0 Intercept	0.517***	0.062**	0.560***	0.063**	0.618***	0.066**
β_1 CO_t						
β_2 NPL_t						
β_3 $LOANHC_t/LOANFV_t$	(0.510)***	(0.048)**	(0.546)***	(0.042)*	(0.604)***	(0.046)
Adj. R^2	0.3981	0.2992	0.3191	0.262	0.2362	0.1746
n	1,008		881		764	
Z-stat	4.66***		3.68***		3.71***	

*, **, *** Indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively.
The sample for Panel A includes 3,801 firm-year observations for the years 2005–2008 and follows Dechow (1994) and runs a "horse race" between $LOANHC_t$ and $LOANFVe_t$ in their abilities to explain CO_{t+1}. As compared to Table 3, Panel A, $LOANFV_t$ has been regressed on the risk-free rate (ten-year Treasury bond yield) to extract the portion of $LOANFV_t$ that relates to interest rates. The residual of that regression, $LOANFVe_t$, is then used in place of $LOANFV_t$ in the tests in Panel A above. The sample for Panel B is made up of 125 firms randomly selected from our main sample for the years 1994–2008. Panel B follows Dechow (1994) and runs a horse race between $LOANHC_t$ and $LOANFV_t$ in their ability to explain cumulative *CO* from CO_{t+1} to CO_{t+x} where *x* is 1, 2, or 3 years from time *t*. Vuong's (1989) Z-statistic tests the null hypothesis that the *LOANHC* model (Model (1)) and the *LOANFV* model (Model (2)) are equally close in their ability to explain cumulative CO_{t+x}. A positive number indicates that $LOANHC_t$ is better at predicting cumulative CO_{t+x}; a negative number indicates that $LOANFV_t$ is better at predicting cumulative CO_{t+x}. Year fixed effects have been included (but are untabulated for brevity) to control for changes in macroeconomic factors over the long time horizon. Panel C performs a similar analysis as that in Panel B using Model (1a) and Model (2a), which are simplified versions of Model (1) and Model (2), respectively. To minimize the influence of outliers, all variables are winsorized at the 1 percent and 99 percent levels. t-statistics are based on standard errors that have been adjusted for clustering by firm.
Variables are as defined in Table 1.

Given the results in Blankespoor et al. (2013) that leverage ratios can have significant explanatory power for predicting bank failures using the fair values for *all* financial instruments, Table 6, Panel B reports results for a similar analysis adjusting leverage ratios only for reported loan fair values given our focus in this study. We use the same control variables and research design as in Blankespoor et al. (2013). Similar to Panel B, we tabulate results using *FAIL2*, but inferences are similar using *FAIL3*. TIER 1, the leverage ratio mainly used by bank regulators is a significant determinant of bank failure with a coefficient of 0.236 ($p < 0.01$), but the leverage ratio adjusted for differences between reported loan fair values and historical costs (FV *LEVERAGE*) is not significantly related to bank failures.

Finally, we graphically examine the evolution of reported loan fair values over time to determine if there is a signal of failure that the regressions miss. For each of the 73 failed banks, we obtain the last year of available financial statement data, which we label year *t*. We then match the failed bank with a non-failing bank with the closest predicted probability of failure in that same year *t* using the prediction model in Equation (7), modified to exclude *FVDIFF* because we do not necessarily want the matched banks to have the same reported loan fair values. In Figure 1, we then plot median *NPL*s, net historical loan values, and reported loan fair values for the three years leading up to year *t*. Year *t* is the last year of available financial statement data, not the year of failure; most failed banks fail at least one year past year *t*. Both failed and non-failed banks have

TABLE 6

Bank Failures

Panel A: Ability of Loans at Historical Cost and Fair Value Difference to Predict Bank Failures

$$\Pr(FAIL2 = 1)_{t+1} = \alpha + \beta_1 EQUITYCAP_t + \beta_2 LOAN\%_t + \beta_3 NPL_t + \beta_4 LIQUIDITY_t + \beta_5 ROA_t + \beta_6 SIZE_t + \beta_7 HOLDINGCO_t + \beta_8 DEPOSIT_t + \beta_9 LOANHC_t + \beta_{10} FVDIFF_t + \varepsilon_t. \quad (7)$$

	Coeff.	Chi-square
Intercept	53.814	4.28**
$EQUITYCAP_t$	−3.094	0.49
$LOAN\%_t$	6.000	9.93***
NPL_t	18.132	7.78***
$LIQUIDITY_t$	0.039	0.05
ROA_t	−0.116	0.71
$SIZE_t$	0.043	0.13
$HOLDINGCO_t$	−0.092	0.06
$DEPOSIT_t$	0.006	9.83***
$LOANHC_t$	−63.970	5.92**
$FVDIFF_t$	−0.601	0.01

(continued on next page)

similar values of *FVDIFF*, the difference between historical costs and fair values, in year *t*–3 and similar decreases in net historical loan values leading up to year *t*. Both groups also have increases in *NPL*s, though the increase in *NPL*s for failed banks appears larger. Interestingly, both failed and non-failed banks experience an *increase* in reported loan fair values in the three years leading up to year *t*, and the increase for failed banks appears larger, approximately twice the increase of non-failed banks on average. This graphical evidence does not suggest that reported loan fair values provide a clear warning signal to users of impending bank failure. In sum, across both our horse race and failure tests, net historical costs clearly outperform reported loan fair values as a predictor of future credit loss fundamentals.

V. WHY DO REPORTED LOAN FAIR VALUES PERFORM POORLY?

This section explores three non-mutually exclusive potential explanations for reported loan fair values performing relatively poorly in predicting future credit loss fundamentals. The first is that fair values for loans are inherently difficult to estimate, either due to a combination of complexities with the fair value measurement and because most loans are rarely sold and thus banks generally lack the experience and expertise to estimate loan fair values. To test this explanation, we first sort banks on the extent to which real estate loans comprise their loan portfolio. Ryan (2007) indicates that mortgages are more likely to be standardized and frequently sold or securitized compared to other loan types. Thus, estimating fair values for real estate loans should generally be less subjective and less difficult relative to other loan types. We also sort banks on the extent to which they have sold loans in the prior year as banks with more experience in selling loans should have more expertise and sophistication when developing loan fair value measures.

TABLE 6 (continued)

Panel B: Ability of Historical Cost, Fair Value, and Tier 1 Capital Ratios to Predict Bank Failures

$$\Pr(FAIL2=1)_{t+1}=\alpha+\beta_1 LEVERAGE_t+\beta_2 NONACCRLOANS_t +\beta_3 PASTDUELOANS_t+\beta_4 OREO_t+\beta_5 ABSMATURITYGAP_t +\beta_6 ROA_t+\beta_7 SIZE_t+\varepsilon_t. \quad (8)$$

	FV *LEVERAGE*		GAAP *LEVERAGE*		TIER 1 *LEVERAGE*	
	Coeff.	**Chi-Square**	**Coeff.**	**Chi-Square**	**Coeff.**	**Chi-Square**
$LEVERAGE_t$	0.014	1.266	0.036	2.584	0.236	10.435***
$NONACCRLOANS_t$	0.490	47.386***	0.496	46.656***	0.495	33.498***
$PASTDUELOANS_t$	0.088	0.012	0.104	0.018	0.140	0.035
$OREO_t$	−0.283	1.431	−0.336	1.922	−0.523	3.624*
$ABSMATURITYGAP_t$	−0.769	0.436	−0.652	0.305	−0.250	0.044
ROA_t	−0.185	4.006**	−0.144	1.665	−0.053	0.134*
$SIZE_t$	0.102	1.120	0.078	0.593	0.041	0.160
n	3,584		3,584		3,584	
Pseudo R^2	0.259		0.262		0.293	

*, **, *** Indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively.
The sample for Panel A includes 3,678 firm-year observations for the years 2005–2008; Panel B contains 3,584 firm-year observations due to the requirement for additional control variables. *FAIL2* (*FAIL3*) is a dichotomous variable set to 1 for year *t* if a bank fails within two (three) years after the availability of year *t*'s financial statements (which is assumed to be three months after year end). There are 73 failed banks in our sample period for which we have data to perform our main analysis in Panel A. Panel A follows Thomson (1991) and estimates a logistic regression to determine whether *FVDIFF* provides incremental information about the probability of bank failure. Panel B follows Blankespoor et al. (2013) and estimates logistic regressions to determine the ability of leverage ratios calculated using fair value of loans, reported GAAP, or Tier 1 capital to predict bank failures. To minimize the influence of outliers, all variables are winsorized at the 1 percent and 99 percent levels. Chi-square statistics are based on standard errors that have been adjusted for clustering by firm.
New variables used in the failure analysis are defined below as follows; all other variables are as defined in Table 1 (firm and year subscripts are omitted).

Variable Definitions:
EQUITYCAP = total book value of equity divided by total gross loans at the end of year *t*;
LIQUIDITY = total liabilities minus total deposits divided by cash plus short-term investments at the end of year *t*;
ROA = return on average assets. Calculated as net income divided by average total assets at the end of year *t*;
SIZE = natural log of total book value of assets, in thousands, at the end of year *t*;
HOLDINGCO = dichotomous variable set to 1 if the bank is set up as a bank holding company, and is 0 otherwise;
DEPOSIT = total deposits, in millions, divided by total number of branches as of the end of year *t*;
LEVERAGE = either the fair value, GAAP, or Tier 1 capital leverage ratio calculated similarly to Blankespoor et al. (2013). GAAP leverage is calculated as total tangible assets and mortgage servicing rights divided by total tangible assets and mortgage servicing rights less total liabilities and preferred equity at the end of year *t*. Fair value leverage is calculated similarly but tangible assets are adjusted to use the fair value of loans. Tier 1 leverage is the inverse of the Tier 1 capital ratio at the end of year *t*;
NONACCRLOANS = loans for which the bank is no longer accruing interest divided by total assets as of the end of year *t*;
PASTDUELOANS = loans over 90 days past due divided by total assets as of the end of year *t*;
OREO = other real estate owned divided by total assets as of the end of year *t*; and
ABSMATURITYGAP = absolute difference between assets and liabilities that are due to mature or be repriced within one year, divided by total assets as of the end of year *t*.

FIGURE 1
Median Loan Variables over Time for Failed and Non-Failed Banks

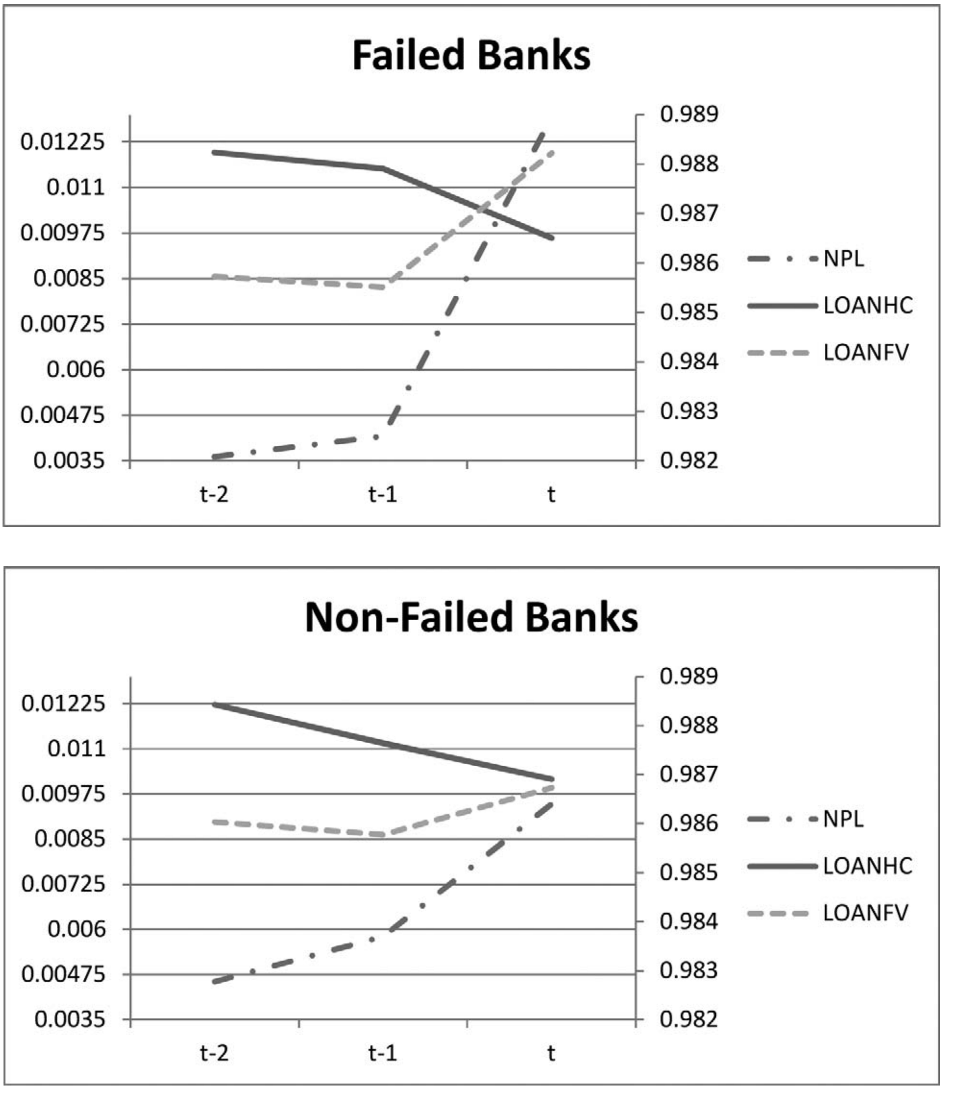

Figure 1 graphically depicts median NPLs, net historical loan values, and reported loan fair values for the three years leading up to the last year a failed bank in our sample has available financial statement data, which we label year *t*, along with a matched sample of banks that do not fail. For each of the 73 failed banks in our sample, we match the failed bank with a non-failing bank in that same year *t* that has the closest predicted probability of failure using the prediction model in Equation (7), modified to exclude *FVDIFF*. We exclude *FVDIFF* from this model because we want failed and matching non-failed banks to have roughly similar economic characteristics, but we do not necessarily want them to have the same loan fair values.

Panel A of Table 7 presents estimates of Equations (1) and (2) using chargeoffs for banks with relatively low and relatively high holdings of real estate loans. Tests in this section focus on predicting chargeoffs for brevity given that prior results are similar for chargeoffs and non-performing loans. Among banks with either a low or high concentration of real estate loans, Equation (1) with *LOANHC* has greater explanatory power than Equation (2) with *LOANFV*. Importantly, however, the Vuong statistic in the high real estate loan subsample is not significantly different from the Vuong statistic in the low real estate loan subsample ($Z = 1.26$). Panel B of Table 7 presents the same type of analysis for banks sorted on the extent of loan sales. Again, there is no

TABLE 7

Subsample Analyses
The Differential Ability of Loans at Fair Values to Predict Future Chargeoffs Across Subsample In Sample

$$CO_{t+1} = \alpha + \beta_1 CO_t + \beta_2 NPL_t + \beta_3 LOANHC_t + \varepsilon_t. \quad (1)$$
$$CO_{t+1} = \alpha + \beta_1 CO_t + \beta_2 NPL_t + \beta_3 LOANFV_t + \varepsilon_t. \quad (2)$$

Panel A: Differential Ability of Loans at Fair Value to Predict Chargeoffs when Real Estate Loan Percentage is Above and Below the Median

	Above Median RE Loan % (n = 1,901)				**Below Median RE Loan % (n = 1,900)**			
	Model (1)		**Model (2)**		**Model (1)**		**Model (2)**	
	Coeff.	**t-stat**	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**
α_0 Intercept	0.594	8.73***	0.036	3.62***	0.559	8.41***	0.042	4.41***
β_1 CO_t	0.258	3.78***	0.467	7.09***	0.277	5.73***	0.433	8.77***
β_2 NPL_t	0.127	7.18***	0.189	9.67***	0.136	6.22***	0.189	8.87***
β_3 $LOANHC_t/LOANFV_t$	(0.597)	−8.70***	(0.034)	−3.41***	(0.563)	−8.37***	(0.039)	−4.09***
	Adj. R^2	0.5078	Adj. R^2	0.4537	Adj. R^2	0.4817	Adj. R^2	0.4450
	Z-stat	4.47***			Z-stat	4.14**		
	Z-stat across subsamples			1.26				

Panel B: Differential Ability of Loans at Fair Value to Predict Chargeoffs when Loan Sales are Above and Below the Median

	Above Median Loan Sales (n = 1,876)				**Below Median Loan Sales (n = 1,873)**			
	Model (1)		**Model (2)**		**Model (1)**		**Model (2)**	
	Coeff.	**t-stat**	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**
α_0 Intercept	0.608	8.46***	0.033	3.34***	0.449	7.11***	0.003	0.30
β_1 CO_t	0.611	6.80***	0.809	8.78***	0.377	5.06***	0.506	6.66***
β_2 NPL_t	0.234	7.61***	0.289	8.86***	0.240	9.93***	0.293	11.66***
β_3 $LOANHC_t/LOANFV_t$	(0.614)	−8.45***	(0.032)	−3.24***	(0.453)	−7.10***	(0.002)	−0.22
	Adj. R^2	0.5578	Adj. R^2	0.5130	Adj. R^2	0.5063	Adj. R^2	0.4621
	Z-stat	4.76***			Z-stat	4.04**		
	Z-stat across subsamples			0.37				

(continued on next page)

TABLE 7 (continued)

Panel C: Differential Ability of Loans at Fair Value to Predict Chargeoffs when Tier 1 Capital is Above and Below the Median

		Above Median Tier 1 Capital (n = 1,870)				Below Median Tier 1 Capital (n = 1,865)			
		Model (1)		Model (2)		Model (1)		Model (2)	
		Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
α_0	Intercept	0.528	9.28***	0.038	4.29***	0.609	8.11***	0.047	4.61***
β_1	CO_t	0.279	5.62***	0.471	8.79***	0.229	4.11***	0.399	7.52***
β_2	NPL_t	0.135	7.12***	0.181	8.85***	0.132	6.29***	0.195	9.51***
β_3	$LOANHC_t/LOANFV_t$	(0.531)	−9.26***	(0.037)	−4.11***	(0.611)	−8.07***	(0.043)	−4.26***
		Adj. R^2	0.4757	Adj. R^2	0.4188	Adj. R^2	0.5042	Adj. R^2	0.4679
		Z-stat	4.78***			Z-stat	3.88***		
		Z-stat across subsamples			1.14				

Panel D: Differential Ability of Loans at Fair Value to Predict Chargeoffs with or without Audit Committee Expertise

		AC Expertise (n = 333)				No AC Expertise (n = 1,668)			
		Model (1)		Model (2)		Model (1)		Model (2)	
		Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
α_0	Intercept	0.374	3.15***	0.043	2.13**	0.627	8.20***	0.025	1.86*
β_1	CO_t	1.052	6.56***	1.228	8.59***	0.475	4.92***	0.649	6.55***
β_2	NPL_t	0.222	4.32***	0.248	5.07***	0.233	7.81***	0.307	9.36***
β_3	$LOANHC_t/LOANFV_t$	(0.376)	−3.14***	(0.042)	−2.09**	(0.632)	−8.19***	(0.024)	−1.78*
		Adj. R^2	0.6865	Adj. R^2	0.6747	Adj. R^2	0.5372	Adj. R^2	0.482
		Z-stat	1.25			Z-stat	4.95***		
		Z-stat across subsamples			−2.03***				

Panel E: Differential Ability of Loans at Fair Value to Predict Chargeoffs when External Auditor is Big N or non-Big N

		Big N Auditor (n = 833)				Non-Big N Auditor (n = 2,366)			
		Model (1)		Model (2)		Model (1)		Model (2)	
		Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
α_0	Intercept	0.354	4.14***	0.032	2.42**	0.555	8.24***	0.007	0.74
β_1	CO_t	0.913	5.23***	1.045	6.31***	0.399	5.62***	0.563	8.12***
β_2	NPL_t	0.216	3.71***	0.249	4.12***	0.245	10.88***	0.308	13.11***
β_3	$LOANHC_t/LOANFV_t$	(0.357)	−4.13***	(0.031)	−2.38**	(0.560)	−8.23***	(0.007)	−0.64
		Adj. R^2	0.6185	Adj. R^2	0.6023	Adj. R^2	0.5068	Adj. R^2	0.4572
		Z-stat	1.99**			Z-stat	5.01***		
		Z-stat across subsamples			−1.92***				

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TABLE 7 (continued)

Panel F: Differential Ability of Loans at Fair Value to Predict Chargeoffs when Analyst Coverage Orthogonal to Size is Above and Below the Median

	Above Median Analyst Coverage (n = 1,146)				Below Median Analyst Coverage (n = 2,644)			
	Model (1)		**Model (2)**		**Model (1)**		**Model (2)**	
	Coeff.	**t-stat**	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**
α_0 Intercept	0.483	5.41***	0.030	2.60***	0.534	9.44***	0.019	2.10**
β_1 CO_t	0.623	5.13***	0.750	6.24***	0.480	6.18***	0.658	8.49***
β_2 NPL_t	0.224	5.66***	0.281	6.85***	0.237	11.00***	0.289	12.56***
β_3 $LOANHC_t/LOANFV_t$	(0.487)	−5.40***	(0.030)	−2.53***	(0.538)	−9.44***	(0.018)	−1.99**
	Adj. R^2	0.5594	Adj. R^2	0.5286	Adj. R^2	0.5150	Adj. R^2	0.4655
	Z-stat	3.17***			Z-stat	8.81***		
	Z-stat across subsamples			−1.24				

*, **, *** Indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively.
Each panel of this table follows Dechow (1994) and runs a "horse race" between $LOANHC_t$ and $LOANFV_t$ in their ability to explain CO_{t+1}. Vuong's (1989) Z-statistic tests the null hypothesis that the *LOANHC* model (Model (1)) and the *LOANFV* model (Model (2)) are equally close in their ability to explain cumulative CO_{t+1}. A positive number indicates that $LOANHC_t$ is better at predicting cumulative CO_{t+1}; a negative number indicates that $LOANFV_t$ is better at predicting cumulative CO_{t+1}. "Z-stat across subsamples" compares the Z-statistic across the two subsamples in each panel. That is, it tests whether the relative difference between the *LOANFV*, and the *LOANHC* models are different across subsamples. A positive number indicates that the relative difference between the *LOANFV* and *LOANHC* models in each subsample is smaller in the subsample presented on the right side of our table for predicting CO_{t+1}; a negative number indicates that the relative difference between the *LOANFV* and *LOANHC* models in each subsample is smaller in the subsample presented on the left side of our table for predicting CO_{t+1}. Panel A presents results separately for the banks above and below the median of real estate loan percentage. Panel B presents results separately for the banks with loan sales above or below median of loan sales. Panel C presents results separately for the banks above and below the median of Tier 1 capital. Panel D presents results separately for the banks with or without audit committee expertise. As discussed in Bédard and Gendron (2010), what constitutes a "financial expert" is subject to debate. The majority of research that has examined audit committee expertise has adopted a more restrictive view of expertise that we follow as compared to the definition of an expert in the Sarbanes-Oxley Act (SOX). We match our firms to the BoardEx database and obtain employment information about the directors of our firms where available and define a director as a financial expert if they are (or have been) professional accountants, treasurers, controllers, financial analysts, academics, or CFOs. We then calculate the percentage of experts for each firm year. It is worth noting that by using this more restrictive definition of experts, the majority of firms in our sample actually have no financial experts in their audit committees. Panel E presents results separately for the banks with or without a Big N external auditor. Panel F presents results separately for the banks with residual analyst coverage (orthogonal to market value of equity) above or below the median. To minimize the influence of outliers, all variables are winsorized at the 1 percent and 99 percent levels. t-statistics are based on standard errors that have been adjusted for clustering by firm.
Variables are as defined in Table 1.

significant difference in the relative predictive ability of reported loan fair values across these groups (Z = 0.37). Thus, the relative predictive ability of reported loan fair values is not significantly worse from that of loan historical costs either in settings where fair values for loans should be inherently more difficult to estimate or for banks that should have more experience and expertise in dealing with loan fair values. Thus, this evidence does not support inherent estimation difficulty or lack of preparer expertise as primary explanations for our findings.

The second explanation we explore is that, consistent with the evidence in Nissim (2003), managers may have incentives to manipulate loan fair value information, which could compromise the predictive ability of reported loan fair values. To test this possibility, we sort banks on their Tier 1 capital ratio because Nissim's (2003) findings suggest that banks with lower capital ratios are more likely to manipulate loan fair values. Results in Table 7, Panel C show that among banks with either a low or high capital ratios, Equation (1) with *LOANHC* has greater explanatory power than Equation (2) with *LOANFV*. However, the Vuong statistic in the high capital ratio subsample is not significantly different from the Vuong statistic in the low capital ratio subsample ($Z = 1.14$). Thus, the relative predictive ability of reported loan fair values is not significantly worse in settings where managers may have more incentives to manipulate loan fair values. Thus, this evidence does not support the "manipulation" theory as a primary explanation for our findings.[19]

The final explanation we explore is that reported loan fair values perform poorly because the fair values are not subject to sufficient scrutiny, potentially because they are only required to be disclosed in the notes and, thus, managers may not put as much effort into estimating these figures. To test this possibility, we sort banks along three dimensions: percentage of financial experts on the audit committee, the use of a Big N auditor, and residual analyst following, which is analyst following orthogonalized to logged market equity. Banks that rank higher along these dimensions face more financial statement scrutiny from audit committees, auditors, and analysts. Results in Table 7, Panel D show that among banks with audit committee expertise, there is no significant difference in explanatory power between the historical cost and loan fair value models ($Z = 1.25$). Among banks with no audit committee expertise, on the other hand, the historical cost model significantly outperforms the fair value model ($Z = 4.95$). Moreover, the Vuong statistic in the expertise subsample is significantly different from the Vuong statistic in the no expertise subsample ($Z = -2.03$), supporting the notion that banks under higher scrutiny offer *relatively* better fair values.

Results for auditor type in Panel E of Table 7 show that the relative predictive ability of reported loan fair values is worse in settings where managers do not face scrutiny from Big N auditors ($Z = -1.92$).[20] Results in Table 7, Panel F show that the greater predictive ability of loan historical costs over reported loan fair values is greater among banks with lower analyst scrutiny ($Z = 8.81$) than banks with higher analyst scrutiny ($Z = 3.17$), but this difference across groups is only marginally significant ($Z = -1.24$, two-sided $p = 0.107$, one-sided $p = 0.053$). Taken as a whole, the evidence from these three tests provides support for lack of scrutiny of reported loan fair values contributing to our main findings. However, we acknowledge that other unobservable factors, such as a lack of managerial ability or talent, may also contribute to the relatively poor predictive ability of loan fair values.

VI. CONCLUSION AND DISCUSSION

This study examines the ability of loan fair values to predict credit losses relative to the ability of net historical costs already recognized under GAAP. Using a broad sample of banks from 2005 to 2009, we find that net historical loans costs are a better overall predictor of credit losses. Our results are consistent across a variety of tests, including in-sample and out-of-sample tests,

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[19] In untabulated analysis, we also do not see support for the manipulation theory using discretionary loan loss reserves following Beaver and Engel (1996) or firms that are considered cherry-pickers with respect to reclassifying other comprehensive income (OCI) gains (losses) into net income (Lee, Petroni, and Shen 2006).

[20] To ensure that our results are not merely proxying for the expertise of the scrutinizing party, rather than the scrutiny itself (i.e., a variant of the expertise explanation), we examine banks audited by KPMG versus other auditors. Kanagaretnam, Krishnan, and Lobo (2009) and Bratten, Causholli, and Myers (2012) characterize KPMG as the banking specialist among auditors, as KPMG audits significantly more banks than any other auditor. If a lack of expertise or training with fair values were a main culprit in our findings, then one would expect loan fair vales to have greater relative predictive ability among banks audited by KPMG. However, we find no significant difference between KPMG-audited banks versus other banks (untabulated), which suggests that the scrutiny of a Big N auditor versus other auditors matters more for loan fair value quality than auditor bank expertise itself.

incremental prediction tests, long-window tests back to the 1990s, and bank failure predictions. However, we acknowledge that inferences may differ in other samples or time periods we do not examine. Overall though, findings from our sample do not support the notion that reported loan fair values provide more useful information for assessing the credit risk of a bank's loan portfolio relative to net historical costs.

We also explore, via subsample analyses, *why* loan fair values fare relatively poorly in predicting credit losses relative to net historical costs. We find no evidence that reported loan fair values' relative performance worsens in settings where loan fair values may be inherently harder to estimate, where banks lack expertise with loan fair values, or where banks have more incentives to manipulate loan fair values. However, we do find evidence that reported loan fair values perform worse in settings where managers face less scrutiny from outside auditors and audit committees. Hence, it appears that reported loan fair values lack reliability and have the potential to improve if managers spend more time and resources to develop high-quality fair values.

Thus, from a policy perspective, requiring that these figures be recognized instead of being disclosed in the notes might improve the reliability and predictive ability of reported loan fair values due to increased scrutiny (Libby et al. 2006). On the other hand, increasing the prominence of loan fair values might actually give preparers greater incentives to manipulate these figures, which could compromise the predictive ability of loan fair values even further. Neither our study nor the prior literature that has used these fair value disclosures can definitively speak to these effects. However, our findings do offer two interesting takeaways for scholars and policymakers. First, given the usefulness of net historical loan costs in predicting credit losses, our findings suggest that any new accounting standard for the reporting of bank loans should retain at least some measurement at net historical cost. Importantly, our comparative tests only establish that net historical costs perform *relatively* better in predicting future credit losses compared to reported loan fair values. Our tests do not imply that measuring loans net of loan loss reserve cannot be improved. In fact, the FASB (2013a) has recently proposed expanding the measurement of the loan loss reserve beyond incurred losses to include all expected credit losses.

Second, compared to net historical costs, reported loan fair values currently reported under U.S. GAAP are not particularly useful for understanding credit risk in banks' loan portfolios. Thus, if reported loan fair values are to aid users in better understanding credit risk, then significant improvements in these figures are needed. In addition to increased scrutiny, providing a reconciliation of the differences between loan fair values and gross loans (e.g., incurred and expected credit losses, changes in discount rates related to credit and non-credit risk) would likely prove useful in assessing the credit quality of banks' loan portfolios.

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