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PREDICTING LOAN LOSS PROVISIONS BY INCLUDING LOAN TYPE CHARACTERISTICS

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ABSTRACT

Researchers examining managerial behavior in the banking industry rely almost entirely on the validity of discretionary loan loss provision models in reaching their conclusions. Very little research analyzes the usefulness and effectiveness of discretionary loan loss provision models. This places our knowledge about managerial discretion in the banking industry on a precarious foundation. This paper evaluates the effectiveness of extant discretionary loan loss provision models and a newly developed model. The new model incorporates loan type variables such as real estate, credit card, commercial, and individual loans. The paper analyzes the models with respect to their explanatory power and the persistence of their discretionary and nondiscretionary components. The new model performs the best in explaining loan loss provisions. All of the variables introduced in the new model are highly significant and the nonperforming credit card loan variable is particularly important, as its coefficient is an order of magnitude larger than other nonperforming loan variables. The new model also produces a discretionary component that has persistence characteristics that are most consistent with managerial discretion. The analysis produces a highly effective new model and provides important evidence on extant loan loss provision models.

JEL: G21, M41

KEYWORDS: Loan Loss Reserves, Loan Loss Provisions, Earnings Manipulation

INTRODUCTION

This paper develops a model of discretionary loan loss provisions and then compares its effectiveness with extant models. The new model incorporates loan types including real estate, commercial, individual, and credit card loans in the analysis. The new model outperforms the other models in terms of goodness of fit and in terms of the expected transitory nature of the discretionary loan loss component. It also performs relatively well in terms of the expected persistence of the nondiscretionary component.

Understanding managerial behavior is a critical component of understanding and interpreting financial statements, evaluating firm and manager performance, and is essential in developing standards and best practices. The earnings management and managerial discretion literature is vast and is growing exponentially. Much of what we have learned about managerial behavior (or at least think we have learned) is based on models of managerial discretion. Kothari (2001) criticizes discretionary accrual models and even provides specific examples where researchers may have misinterpreted the data because of discretionary models. This is despite the fact that accrual models have been analyzed extensively in the literature and researchers have essentially reached a consensus on the preferred model. Banking managerial discretion studies rely on a much more precarious foundation. First, there is no agreement on a preferred model and most banking studies develop their own discretionary models. Second, very little research has examined the validity of these models. Research into discretionary loan loss provision models is essential in order to establish the validity, usefulness, and limitations of these models. This evaluation is critical to improve our understanding and interpretation of previous research and to guide future research on managerial behavior in the banking industry.

This paper extends the literature in several ways. First, it develops a new model of discretionary loan loss provisions incorporating information from specific loan types. Second, it examines the effectiveness of extant discretionary loan loss provision models in terms of goodness of fit and in terms of the expected persistence properties of both the discretionary and nondiscretionary components from these models. Finally, the sample used in this paper is more extensive. Most previous studies have examined only the largest banks as they have relied on the Compustat database. This study examines all U.S. banks with more than one million dollars in assets. The results provide an understanding of a broader sample of banks as compared to most other studies.

The rest of the paper proceeds as follows. Section two provides a review of the managerial discretion literature in the banking industry and of the literature examining models of discretionary behavior by managers. The next section describes the methodology of the paper, the data used for the analysis, and the sample selection process. The next section presents and discusses the empirical results. The last section summarizes and concludes the paper.

LITERATURE REVIEW

Understanding managerial behavior and discretion is critical to understanding and interpreting the financial statements. There is a vast literature on how the financial statements are affected by the way managers respond to different types of incentives and situations. Managing accounting accruals is a significant branch of this research. Early studies focus on accruals. Healy (1985) finds that managers manipulate accruals to maximize their bonus compensation and DeAngelo (1988) argues that managers use their discretion to increase earnings during proxy contests. One criticism of these early earnings management papers is that total accruals are not an adequate proxy for manipulation. Accruals vary with firm operating variables such as sales, depreciation, and other accounts even in the absence of earnings manipulation. Using total accruals as a proxy for manipulation reduces the power of tests and increases the possibility that results are due to economy wide fluctuations and not managerial discretion.

Researchers now use sophisticated techniques to separate accruals into discretionary and nondiscretionary components. Jones (1991) develops a regression model to isolate the discretionary component of accruals in order to examine earnings manipulation in firms seeking import relief. Her methodology and variants of it have become the standard of accrual manipulation research.

Researchers examining managerial discretion in the banking industry focus predominantly on one particular accrual—loan loss provisions. Bank managers respond to earnings incentives just like other managers, but because of bank regulation, they also respond to capital management concerns. The loan loss provision account is of particular interest to bank researchers because it affects both earnings and capital. It is also by far the largest accrual in the banking industry. Loan loss provisions are used to proxy for managerial discretion in earnings smoothing, managerial signaling, and capital management studies.

Earnings smoothing is a popular topic for banking industry earnings management studies. Earnings smoothing occurs when managers "borrow" earnings during good years by increasing loan loss provisions. When earnings are poor managers draw down loan loss allowances which reduces the loan loss provision and increases earnings. Many studies conclude that managers use their discretion over the loan loss provision account to smooth earnings. Kanagaretnam, Matheiu, and Lobo (2003) find that managers smooth earnings in U.S. banks. Perez, Salas, and Salas-Fumas (2008) find earnings smoothing in Spanish banks, Bouvatier, Lepetit, and Strobel (2014) find it in European commercial banks with concentrated ownership, and Handorf and Zhu (2006) in middle-sized banks only. Kanagaretnam, Yang, and Lobo

(2004) find that smoothing evidence is stronger when earnings are extreme. Gebhardt and Novotny-Farkas (2011) find that IAS 39 reduced managers' ability to smooth income. Kilic, Lobo, Ranasinghe, and Sivaramakrishnan (2013) suggest that SFAS increased income smoothing using loan loss provisions. This is just a partial list of the many studies that examine earnings smoothing in banks.

A number of studies also conclude that managers use discretion over the loan loss provision account to signal their private information to investors. Ahmed, Takeda, and Thomas (1999) find that managers use loan loss provisions to manage capital ratios but not for signaling. Kanagaretnam, Yang, and Lobo (2004) show that bank managers use the loan loss provision account to both signal and to smooth earnings. Kanagaretnam, Yang, and Lobo (2005) find that managers in smaller banks and in banks with greater earnings variability are better able to signal their private information. Kanagaretnam, Krishnan, and Lobo (2009) show that managers' ability to signal depends on the industry expertise of their auditors.

The validity of these studies and their conclusions depends almost entirely on the validity of discretionary loan loss provision models. Despite this crucial dependence, very little research has examined discretionary loan loss provision models. Several working papers evaluate discretionary loan loss provision models but I am not aware of any published studies in this area. Medeiros, Dantas, and Lustosa (2012) examine the effectiveness of eleven discretionary loan loss provision models in terms of goodness of fit and their transitory properties using Brazilian bank data. Beatty and Liao (2013) do a factor analysis on 9 discretionary loan loss provision models. They find only three separate statistically significant factors from all of the variables used in these models. They formulate four models to represent the 9 models that they study and to isolate each of the factors contained in these models. Beatty and Liao (2013) provide evidence that all of the models have some ability to identify extreme earnings management from bank restatements and SEC comment letters.

Many studies examine the discretionary accrual models used outside of the banking literature. Dechow, Sloan, and Sweeney (1995) examine the power and specification of five different accrual models. They conclude that the modified-Jones model outperforms the other models in terms of both power and specification. Dechow, Hutton, Kim, and Sloan (2011) find that incorporating reversals increases the power of earnings management tests by forty percent. Guay, Kothari, and Watts (1996) find that none of the five discretionary accrual models they examine effectively isolates managerial discretion. Jones, Krishnan, and Melendrez (2008) find that discretionary accrual models detect fraudulent earnings events and non-fraudulent earnings restatements. Collins and Hribar (2002) and Hansen (2002) both show that the presence of mergers, acquisitions, and discontinued operations bias discretionary accrual models. These results suggest that accrual models are able to detect extreme earnings management but are not very effective in isolating smaller amounts of managerial discretion.

Researchers have expressed concern about conclusions drawn from the accrual management literature despite the amount of research examining discretionary accrual models. Kothari (2001) points out possible misinterpretations from four studies that examine earnings management during the time period leading up to an IPO. He demonstrates that the most popular discretionary accrual model—the modified-Jones model, results in an incorrect prediction of manipulation when legitimate revenue growth from credit sales is present. He calls for an improvement in models and tests in the earnings management literature. The need for improved models and a more thorough examination of existing models is even more critical in the banking industry. Unlike discretionary accrual models, very little research has examined the effectiveness and potential problems in discretionary loan loss provision models The concern that researchers have misinterpreted tests of managerial discretion in the banking industry looms large because of the lack of research into these models. This paper attempts to add to the scant knowledge we have about the effectiveness of these models.

DATA AND METHODOLOGY

This paper compares the effectiveness of extant discretionary loan loss provision models to the effectiveness of a newly developed model that includes loan type variables. First, I describe several extant discretionary loan loss provision models. Second, I develop a model of discretionary loan loss provisions by adding loan type variables. Next, I compare how well the models predict loan loss provisions. Then I use several tests to compare the persistence characteristics of both the discretionary and nondiscretionary components from the models. Earnings persistence and the persistence of loan loss provisions for both the discretionary and nondiscretionary components from each model are tested. I also examine the persistence of the discretionary loan loss provision.

Beatty and Liao (2013) perform a factor analysis on nine extant discretionary loan loss provision models. They find that three significant factors capture the essence of all nine models. They construct four models based on their factor analysis. Since their four models isolate all of the statistically significant factors from a broad partition of the literature, I evaluate their four models in order to consolidate my analysis without sacrificing relevance. Their first model is based on Liu and Ryan (2006) and Bushman and Williams (2012). Nonperforming assets, size, and macroeconomic variables explain one of the factors that in my opinion represents the state of the economy. The second model is based on Wahlen (1994), Beatty, Chamberlain, and Magliolo (1995), and Collins, Shackelford, and Wahlen (1995). This model includes the lagged loan loss allowance variable. Their third model is based on Beaver and Engel (1996), Kim and Kross (1998), Kanagaretnam, Krishnan, and Lobo (2010), and Beck and Narayanmoorthy (2013). These models all include the net charge off variable. Beatty and Liao (2013) then construct their own model that captures all of the relevant factors in one model.

<u>Discretionary Loan Loss Provision Models</u>

I examine the validity and effectiveness of extant discretionary loan loss provision models using the four regression models shown in equations 1-4.

$$\begin{aligned}\mathrm{LLP}_t = {} & \alpha_0 + \alpha_1\Delta\mathrm{NPA}_{t+1} + \alpha_2\Delta\mathrm{NPA}_{t} + \alpha_3\Delta\mathrm{NPA}_{t-1} + \alpha_4\Delta\mathrm{NPA}_{t-2} + \alpha_5\Delta\mathrm{Loans}_t \\ & + \alpha_6\mathrm{SIZE}_{t\text{-}1} + \alpha_7\Delta\mathrm{GDP}_t + \alpha_8\mathrm{CSRET}_t + \alpha_9\Delta\mathrm{UE}_t + \varepsilon_t\end{aligned} \tag{1}$$

$$\begin{aligned}\mathrm{LLP}_t = {} & \alpha_0 + \alpha_1\Delta\mathrm{NPA}_{t+1} + \alpha_2\Delta\mathrm{NPA}_{t} + \alpha_3\Delta\mathrm{NPA}_{t-1} + \alpha_4\Delta\mathrm{NPA}_{t-2} + \alpha_5\Delta\mathrm{Loans}_t \\ & + \alpha_6\mathrm{SIZE}_{t\text{-}1} + \alpha_7\Delta\mathrm{GDP}_t + \alpha_8\mathrm{CSRET}_t + \alpha_9\Delta\mathrm{UE}_t + \alpha_{10}\mathrm{LLA}_{t\text{-}1} + \varepsilon_t\end{aligned} \tag{2}$$

$$\begin{aligned}\mathrm{LLP}_t = {} & \alpha_0 + \alpha_1\Delta\mathrm{NPA}_{t+1} + \alpha_2\Delta\mathrm{NPA}_{t} + \alpha_3\Delta\mathrm{NPA}_{t-1} + \alpha_4\Delta\mathrm{NPA}_{t-2} + \alpha_5\Delta\mathrm{Loans}_t \\ & + \alpha_6\mathrm{SIZE}_{t\text{-}1} + \alpha_7\Delta\mathrm{GDP}_t + \alpha_8\mathrm{CSRET}_t + \alpha_9\Delta\mathrm{UE}_t + \alpha_{11}\mathrm{NCO}_t + \varepsilon_t\end{aligned} \tag{3}$$

$$\begin{aligned}\mathrm{LLP}_t = {} & \alpha_0 + \alpha_1\Delta\mathrm{NPA}_{t+1} + \alpha_2\Delta\mathrm{NPA}_{t} + \alpha_3\Delta\mathrm{NPA}_{t-1} + \alpha_4\Delta\mathrm{NPA}_{t-2} + \alpha_5\Delta\mathrm{Loans}_t \\ & + \alpha_6\mathrm{SIZE}_{t\text{-}1} + \alpha_7\Delta\mathrm{GDP}_t + \alpha_8\mathrm{CSRET}_t + \alpha_9\Delta\mathrm{UE}_t + \alpha_{10}\mathrm{LLA}_{t\text{-}1} + \alpha_{11}\mathrm{NCO}_t + \varepsilon_t\end{aligned} \tag{4}$$

I scale the following variables by lagged total loans in order to mitigate heteroskedasticity:

LLP	Loan loss provisions
ΔNPA	Change in Non-Accrual Loans and Loans 90 days or more past due from the previous quarter.
ΔLoans	Change in total loans from the previous quarter.

LLA	Loan loss allowance at the beginning of the quarter.
NCO	Net Charge offs (total charge offs minus total recoveries)

The remaining variables are

SIZE	Natural log of total assets
ΔGDP	Percentage change in GDP over the quarter
CSRET	Return on the Case-Shiller Real Estate Index during the quarter
ΔUE	Percentage change in unemployment rate during the quarter.

In addition to testing the 4 extant models, I create a new model that includes loan type variables. I compare the new model shown in equation 5 with the previous four models.

$$\begin{aligned} LLP_t = {} & \alpha_0 + \alpha_1 \Delta NPA_{t+1} + \alpha_2 \Delta NPA_t + \alpha_3 \Delta NPA_{t-1} + \alpha_4 \Delta NPA_{t-2} + \alpha_5 \Delta Loans_t + \alpha_6 SIZE_{t-1} + \alpha_7 \Delta GDP_t + \alpha_8 CSRET_t \\ & + \alpha_9 \Delta UE_t + \alpha_{10} LLA_{t-1} + \alpha_{11} NCO_t + \alpha_{12} \Delta NPCC_t + \alpha_{13} \Delta NPRE_t + \alpha_{14} \Delta NPCOM_t + \alpha_{15} \Delta NPIND_t + \varepsilon_t \end{aligned} \tag{5}$$

The additional loan type variables shown in this model are:

ΔNPCC	Change from the previous quarter in non-accrual credit card loans and credit card loans 90 days or more past due.
ΔNPRE	Change from the previous quarter in non-accrual real estate loans and real estate loans 90 days or more past due.
ΔNPCOM	Change from the previous quarter in non-accrual commercial loans and commercial loans 90 days or more past due.
ΔNPIND	Change from the previous quarter in non-accrual individual loans (other than credit card loans) and individual loans 90 days or more past due.

The purpose of all of the above models is to separate loan loss provisions into discretionary and nondiscretionary components. The adjusted r-squared from each model is compared to determine which of the models does the best job of predicting loan loss provisions. This is the first test. For subsequent tests, the fitted value from each regression is the proxy for the nondiscretionary component of loan loss provisions. The residual from each regression is the proxy for discretionary loan loss provisions.

Discretionary and nondiscretionary components of loan loss provisions have predictable persistence characteristics. If managers use their discretion to increase (decrease) earnings in the current quarter then future earnings will be lower (higher) by an amount equal to the original discretion. The loan loss provision is a component of earnings so if managers use their discretion to increase (decrease) the loan loss provision in the current quarter then the loan loss provision will be naturally lower (higher) by an equal amount in future quarters. This suggests that as a component of earnings, and as a component of the loan loss provision, the discretionary loan loss provision should be more transient than the nondiscretionary component. One measure of how well the models isolate discretion is how closely their discretionary and nondiscretionary components conform to their expected characteristics.

Persistence Tests

This paper uses three different tests to examine the transitory nature of the discretionary component of loan loss provisions from each of the discretionary loan loss provision models. Two of those three tests simultaneously test the nondiscretionary component. The models are rated according to the lack of persistence of the discretionary component and the presence of persistence for the nondiscretionary component. First, I test the earnings persistence of the discretionary and nondiscretionary loan loss provisions using equation 6.

$$PPP_{t+1} = \alpha_0 + \alpha_1 PPP_t + \alpha_2 NDLLP_t + \alpha_3 DLLP_t + \varepsilon_\tau \quad (6)$$

Where:

PPP represents preprovision profit, which is operating profit without including the loan loss provision. Another definition is net income before taxes, extraordinary items, discontinued operations, and the loan loss provision. It is scaled by total loans.

NDLLP is the fitted value from the discretionary loan loss provision model being tested

DLLP is the residual from the discretionary loan loss provision model being tested.

All of the variables are scaled by lagged total loans. Preprovision profit is scaled directly. The discretionary and nondiscretionary loan loss provisions are scaled indirectly since they are derived from models where the dependent and independent variables have been scaled by total loans.

The second test of persistence is a regression of future loan loss provisions on the discretionary and nondiscretionary components of the loan loss provision. These variables have been previously defined. Models with larger coefficients on nondiscretionary loan loss provisions and smaller or more negative coefficients on discretionary loan loss provisions are consistent with isolating a greater proportion of managerial discretion. Equation 7 describes the persistence test using loan loss provisions.

$$LLP_{t+1} = \alpha_0 + \alpha_1 NDLLP_t + a_2 DLLP_t + \varepsilon_\tau \quad (7)$$

The final test of persistence is a vector autoregression of the discretionary loan loss provision as shown in equation 8. A vector autoregression of nondiscretionary loan loss provision is not performed because it is not clear what the persistence properties of nondiscretionary loan loss provisions should be in a vector autoregression. The discretionary component in this test should produce a negative coefficient. As stated before, if managers use their discretion in the current period to increase (decrease) earnings by lowering (increasing) the loan loss provision account then at some future point the same account must be increased (decreased). All of the reversal from managerial discretion should show up in the discretionary loan loss component since managers have some control over this component. They have less control over the nondiscretionary component that is based on the size and credit quality of the loan portfolio and this depends primarily on customer and macroeconomic characteristics.

$$DLLP_{t+1} = \alpha_0 + \alpha_1 DLLP_t + \varepsilon_\tau \quad (8)$$

Data and Sample Selection

The Federal Deposit Insurance Corporation (FDIC) collects quarterly reports for all FDIC insured institutions including Bank Call Reports and Thrift Financial Reports. This data is currently available on their website for quarters starting in the fourth quarter of 1992. I collected data from all quarters starting with 1992 quarter 4 through 2013 quarter 3 for this study. The data can be collected for individual banks, bank groups, and for all reporting banks. I collected data for all reporting banks using the following URL: www2.fdic.gov/sdi/download_large_list_outside.asp.

The following selection criteria are used to arrive at the study's final sample. First, call report data must be available for all of the variables used in the analysis. Second, lagged loans must be at least $1 million. Third, the following variables are excluded if their magnitudes exceeded (plus or minus) 100% of the total value of lagged loans: loan loss provisions, changes in nonperforming assets (including the lead and lagged values), change in loans, loan loss allowance, and net charge offs. Requirements 2 and 3 are included to mitigate potential heteroskedasticity problems and to reduce the possibility that data errors are included in the analysis. Requirements 2 and 3 do not materially affect the results of the study.

Call report data is available for 823,016 bank-quarter observations from 1992 quarter 4 thru 2013 quarter 3. There are 729,638 bank-quarter observations with data for all of the variables available in the study. Of the 93,378 lost observations approximately a third are due to the need for lead and lagged values in the analysis. The remaining observations are lost because not all banks report all data items every quarter. Additionally, the size requirement excluded 1,265 observations and 1,445 observations are excluded because of extreme data values. The final sample contains 726,928 bank-quarter observations.

Table 1: Descriptive Statistics for Variables Used in the Discretionary Loan Loss Provision Models

	Mean	Minimum	25th Percentile	Median	75th Percentile	Maximum	Standard Deviation
LLP_t	0.0012	-0.5380	0.0000	0.0005	0.0012	0.3522	0.0041
ΔNPA_{t+1}	0.0002	-0.6380	-0.0018	0.0000	0.0019	0.9865	0.0103
ΔNPA_t	0.0002	-0.6380	-0.0018	0.0000	0.0019	0.5168	0.0097
ΔNPA_{t-1}	0.0003	-0.6380	-0.0018	0.0000	0.0019	0.8578	0.0100
ΔNPA_{t-2}	0.0003	-0.6380	-0.0018	0.0000	0.0019	0.9865	0.0102
$\Delta LOAN_t$	0.0242	-0.9998	-0.0094	0.0161	0.0455	0.9999	0.0768
$SIZE_t$	11.6433	7.5622	10.7366	11.4854	12.3368	21.3901	1.3640
ΔGDP_t	0.0116	-0.0200	0.0093	0.0121	0.0157	0.1297	0.0067
$CSRET_t$	0.0095	-0.0736	-0.0020	0.0127	0.0280	0.0716	0.0264
ΔUE_t	0.0000	-0.0107	-0.0017	-0.0010	0.0007	0.0140	0.0030
LLA_{t-1}	0.0156	0.0000	0.0105	0.0135	0.0180	0.9123	0.0110
NCO_t	0.0010	-0.3282	0.0000	0.0001	0.0008	0.5113	0.0036
$\Delta NPCC_t$	0.0000	-0.0791	0.0000	0.0000	0.0000	0.1596	0.0007
$\Delta NPRE_t$	0.0002	-0.6380	-0.0010	0.0000	0.0011	0.3707	0.0078
$\Delta NPCOM_t$	0.0000	-0.5414	-0.0002	0.0000	0.0001	0.4186	0.0047
$\Delta NPIND_t$	0.0000	-0.1817	-0.0001	0.0000	0.0001	0.1844	0.0016

Table 1 shows descriptive statistics for the variables used in the discretionary loan loss provision models. The data includes 726,928 observations during the period 1992 quarter 4 through 2013 quarter 3. All variables except for size and the macroeconomic variables (GDP, CSARET, UE) are deflated by lagged loans and are excluded if they exceed a magnitude of 100% of lagged loans. For example, the mean of LLP is .0012 suggesting that on average loan loss provisions are 0.12% of lagged loans.
LLP: Loan Loss Provision
ΔNPA *: Change in Nonaccrual Loans and Loans 90 days or more past due from the previous quarter.*
ΔLOAN *: Change in total loans from the previous quarter.*
SIZE: Natural logarithm of total assets
ΔGDP *: Percentage Change in gross domestic product during the quarter*
CSRET: Return on the Case-Shiller Real Estate Index during the quarter,
ΔUE *: Change in unemployment during the quarter*
LLA: Loan loss allowance at the beginning of the quarter.
NCO: Net charge offs during the quarter.
ΔNPCC *: Change in Nonaccrual Credit Card Loans and Credit Card Loans 90 days or more past due from the previous quarter.*
ΔNPRE *: Change in Nonaccrual Real Estate Loans and Real Estate Loans 90 days or more past due from the previous quarter.*
ΔNPCOM *: Change in Nonaccrual Commercial Loans and Commercial Loans 90 days or more past due from the previous quarter.*
ΔNPIND *: Change in Nonaccrual Individual Loans and Individual Loans 90 days or more past due from the previous quarter.*

Table 1 provides descriptive statistics for the variables used in the discretionary loan loss provision models. The data period covers from 1992 quarter 4 through 2013 quarter 3. However, because of the need for lead and lagged variables the observations in the study range from 1993 quarter 2 through 2013 quarter 2. There are 726,928 observations for all of the variables. The macroeconomic variables are expressed in percentage change terms, the size variable is in logarithmic form, and all of the other variables are expressed as a proportion of lagged loans. Row 1 of table 1 shows that the mean of loan loss provision is 0.0012. This suggests that on average the loan loss provision is 0.12% of lagged loans. The macroeconomic variables are expressed as a percentage change during the quarter. The mean of ΔGDP is 0.0116 suggesting that GDP has increased on average by 1.16% per quarter during this period. The mean of SIZE is expressed as the natural logarithm of total assets. All of the firm specific variables (except for SIZE) have minimums and maximums that are less than plus or minus one hundred percent of lagged loans since observations with values greater than this were excluded.

RESULTS

Table 2 provides the regression results from equations 1-5. All of the discretionary loan loss provision models are well specified. All of the variables in all of the models are highly significant and all variables except for one have the expected sign. The loan quality variable ΔNPA, including its lead and lagged values are all positively related to loan loss provisions (LLP). An increase in nonperforming loans corresponds to a deterioration of loan quality. This causes managers to increase loan loss provisions.

A discussion of the results from Model 1 in Table 2 follows. The same general discussion applies to all of the models. The coefficient of 0.0336 on ΔNPA shown in the first column of regression results suggests that on average managers increase the loan loss provision by 3.36 cents for every dollar increase in nonperforming loans. In other words, managers expect that about 3.36% of increases in nonperforming loans will be uncollectible. Changes to the size of the loan portfolio are also positively related to loan loss provisions. The coefficient of 0.001 on ΔLoans suggests that managers expect that 0.1% of new loans will be uncollectible and thus the loan loss provision is increased by this amount. The SIZE variable is positively related to loan loss provisions suggesting that on average larger banks deduct a higher proportion of loans from income through the loan loss provision account.

The macroeconomic variables are all highly significant and have the expected sign. The coefficient on ΔGDP of -0.0116 suggests that an increase in GDP over the quarter is associated with managers lowering the loan loss provision account. The coefficient of 0.0007 on ΔUE suggests that managers increase the loan loss provision accounting when unemployment increases. Finally the coefficient of -0.0046 on CSRET suggests that managers decrease the loan loss provision account when the value of real estate increases. Taken together these results suggest that as the economy improves managers lower the loan loss provision account since they expect to collect on a higher proportion of loans when the economy is doing well.

The loan loss allowance account (LLA) coefficient switches signs between regression models 2 and 4. The coefficient on loan loss allowance in Model 2 is 0.062. It is positive and highly significant. In Model 4, the coefficient on loan loss allowance is -0.0103 and it is negative and highly significant. The difference between the two models is the inclusion of net charge offs (NCO). The loan loss allowance account proxies as another loan quality variable in Model 2. Managers that expect more future charge offs will need a larger loan loss allowance and so more current loan loss provisions will be needed to maintain the larger loan loss allowance.

In Model 4 the loan loss account proxies for the size and adequacy of the loan loss allowance account and not for expected charge offs (because charge offs are included in the regression). A larger loan loss allowance account suggests that it is more adequate to the amount of future charge offs. Since the regression in Model 4 includes charge offs, a larger loan loss allowance account suggests that reserves are more adequate to represent future charge offs and so need less replenishing through the loan loss provision account. The inclusion of charge offs causes the coefficient on loan loss allowance in Model 4 to switch signs.

Table 2: Models of Discretionary Loan Loss Provisions

	Model 1	Model 2	Model 3	Model 4	New Model with Loan Types
Intercept	-0.0010	-0.0021	-0.0001	0.0001	-0.0000
	(-23.4)***	(-50.0)***	(-2.3)**	(4.1)***	(-1.6)
ΔNPA_{t+1}	0.0121	0.0159	0.0158	0.0152	0.0155
	(26.5)***	(35.1)***	(47.7)***	(45.9)***	(47.1)***
ΔNPA_{t}	0.0336	0.0375	0.0570	0.0566	0.0258
	(68.1)***	(76.9)***	(158.8)***	(157.8)***	(18.3)***
ΔNPA_{t-1}	0.0427	0.0405	0.0209	0.0210	0.0209
	(89.6)***	(86.2)***	(60.3)***	(60.7)***	(60.7)***
ΔNPA_{t-2}	0.0318	0.0321	0.0126	0.0123	0.0127
	(68.8)***	(70.3)***	(37.4)***	(36.6)***	(38.1)***
$\Delta LOAN_{t}$	0.0010	0.0012	0.0040	0.0040	0.0036
	(16.0)***	(20.4)***	(88.7)***	(88.6)***	(81.8)***
$SIZE_{t}$	0.0002	0.0002	0.0000	0.0000	0.0000
	(58.5)***	(62.4)***	(17.0)***	(15.6)***	(16.6)***
ΔGDP_{t}	-0.0116	-0.0078	-0.0047	-0.0052	-0.0045
	(-11.5)***	(-7.8)***	(-6.4)***	(-7.1)***	(-6.1)***
$CSRET_{t}$	-0.0046	-0.0043	-0.0015	-0.0015	-0.0015
	(-22.5)***	(-21.7)***	(-10.1)***	(-10.1)***	(-10.0)***
ΔUE_{t}	0.0007	0.0009	0.0004	0.0003	0.0004
	(32.3)***	(41.9)***	(24.3)***	(22.0)***	(25.7)***
LLA_{t-1}		0.0620		-0.0103	
		(146.9)***		(-31.9)***	
NCO_{t}			0.7855	0.7946	0.7866
			(810.4)***	(786.5)***	(818.6)***
$\Delta NPCC_{t}$					0.5584
					(105.3)***
$\Delta NPRE_{t}$					0.0226
					(15.3)***
$\Delta NPCOM_{t}$					0.0540
					(34.2)***
$\Delta NPIND_{t}$					0.0141
					(5.2)***
Adjusted R-squared	0.0357	0.0635	0.4934	0.4941	0.5034

Table 2 shows the regression results for the five discretionary loan loss provision models (equations 1-5) examined. The dependent variable LLP is loan loss provisions. Model 5 is shown. The other models contain a subset of the variables in model 5.

$$LLP_t = \alpha_0 + \alpha_1 \Delta NPA_{t+1} + \alpha_2 \Delta NPA_t + \alpha_3 \Delta NPA_{t-1} + \alpha_4 \Delta NPA_{t-2} + \alpha_5 \Delta Loans_t + \alpha_6 SIZE_{t\text{-}1} + \alpha_7 \Delta GDP_t + \alpha_8 CSRET_t + \alpha_9 \Delta UE_t + \alpha_{10} LLA_{t\text{-}1} + \alpha_{11} NCO_t + \alpha_{12} \Delta NPCC_t + \alpha_{13} \Delta NPRE_t + \alpha_{14} \Delta NPCOM_t + \alpha_{15} \Delta NPIND_t + \varepsilon_t$$

*This analysis regresses loan loss provisions on variables other than managerial discretion that should affect it, including variables representing the credit quality of the loan portfolio and macroeconomic variables showing that state of the economy. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.*

LLP: Loan Loss Provision
ΔNPA *: Change in Nonaccrual Loans and Loans 90 days or more past due from the previous quarter.*
ΔLOAN *: Change in total loans from the previous quarter.*
SIZE: Natural logarithm of total assets
ΔGDP *: Percentage Change in gross domestic product during the quarter*
CSRET: Return on the Case-Shiller Real Estate Index during the quarter,
ΔUE *: Change in unemployment during the quarter*
LLA: Loan loss allowance at the beginning of the quarter.
NCO: Net charge offs during the quarter.
ΔNPCC *: Change in Nonaccrual Credit Card Loans and Credit Card Loans 90 days or more past due from the previous quarter.*
ΔNPRE *: Change in Nonaccrual Real Estate Loans and Real Estate Loans 90 days or more past due from the previous quarter.*
ΔNPCOM *: Change in Nonaccrual Commercial Loans and Commercial Loans 90 days or more past due from the previous quarter.*
ΔNPIND *: Change in Nonaccrual Individual Loans and Individual Loans 90 days or more past due from the previous quarter.*

The most significant variable in the regressions, by far, is the net charge off variable (NCO). As we go from Model 1 to Model 3 the inclusion of net charge offs increases the adjusted r-squared from 0.0357 to

0.4934. The coefficient of 0.7855 suggests that for every dollar of net charge offs the loan loss provision account increases by 78.55 cents.

The new loan type variables introduced in Model 5 are all highly significant. The new variables represent changes to the nonperforming loans in the specific categories of credit cards (ΔNPCC), real estate (ΔNPRE), commercial loans (ΔNPCOM), and individual loans (ΔNPIND). The coefficient on changes in nonperforming credit card loans 0.5844, is ten times as high as the coefficients on commercial loans and more than 25 times as high as the coefficient on real estate and individual loans. This dramatic difference highlights the importance of including different loan types separately in the analysis. The lower coefficients on nonperforming real estate and individual loans make sense since most of these loans require collateral. Essentially all real estate loans require the real estate property as collateral. Most individual loans (since credit card loans are accounted for separately) are automobile loans where the loan is collateralized with the vehicle.

The adjusted r-squared value from table 2 is the primary result used to compare the ability of the models to capture the information contained in loan loss provisions. The new model including loan types has the highest adjusted r-squared which is 0.5034. Models 3 and 4 that also include the net charge off variable are close behind with adjusted r-squareds of 0.4934, and 0.4941, respectively. Models 1 and 2 do not perform nearly as well with respect to adjusted r-squared. This is attributed to the lack of net charge offs in these models.

The remaining tables all examine results for the persistence of the discretionary and nondiscretionary components of loan loss provisions from each of the models. The models are rated based on how negative the discretionary component coefficients are and how positive the nondiscretionary component coefficients are in the persistence tests. Table 3 shows the results of regressing future earnings on current earnings components. The purpose of this regression is to examine the earnings persistence properties of the discretionary and nondiscretionary loan loss provision components. If the discretionary loan loss provision model isolates managerial discretion then the nondiscretionary loan loss provision component should be positive and significant and the discretionary loan loss provision component should be negative and significant.

All of the models reported in Table 3 have positive and highly significant coefficients on the preprovision profit variable. This is expected but not part of the persistence tests. Model 2 performs the best with respect to the earnings persistence of the nondiscretionary component. The coefficient on nondiscretionary loan loss provision is 0.2559 and is highly significant. Models 3-5 also produce positive and highly significant coefficients for nondiscretionary loan loss provision. The main test performed in Table 3 is an analysis of the persistence or actually the lack of persistence of the discretionary component of loan loss provision (DLLP). When managers use discretion to increase (decrease) the loan loss provision they are essentially lending (borrowing) from the loan loss allowance and that will naturally reverse at some future time. The discretionary loan loss provision should be negative if the models are completely isolating discretion. Model 3 is the only model that produces a negative and significant coefficient (-0.0078) on the discretionary loan loss provision. The new model I introduce also has a negative coefficient but it is not statistically significant at conventional levels. Since the models isolate a portion of discretion but do not completely isolate the discretionary behavior, the discretionary loan loss provision component represents a combination of discretionary and nondiscretionary components. Consequently, the coefficient on the discretionary loan loss provision component should be a weighted average of the pure discretionary coefficient and the nondiscretionary component coefficient. Thus, one measure of the effectiveness of the different models in isolating discretion is the extent that the coefficient on the discretionary component is less than the nondiscretionary component coefficient. Based on this analysis Model 3 isolates the greatest proportion of discretion and Model 5 (the new model introduced in this paper) is second best. The results in Table 3 are consistent with all of the models with the exception of model 1 isolating a portion of discretionary behavior.

Table 3: Earnings Persistence Test. Regression of Future Pretax Pre-provision Profit on Pretax Earnings Components

Model	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	0.0017 (75.7)***	0.0013 (68.1)***	0.0015 (110.0)***	0.0015 (110.5)***	0.0015 (110.6)***
PPP	0.7700 (875.8)***	0.7689 (873.4)***	0.7701 (876.1)***	0.7701 (876.2)***	0.7700 (875.9)***
NDLLP	-0.1110 (-7.4)***	0.2559 (22.6)***	0.0414 (10.2)***	0.0351 (8.6)***	0.0373 (9.3)***
DLLP	0.0212 (7.3)***	0.0003 (0.1)	-0.0078 (-1.9)**	-0.0017 (-0.4)	-0.0047 (-1.2)
Adjusted R-squared	0.5138	0.5141	0.5138	.5138	0.5138

Table 3 shows the results of regressing the future values of pretax provision profits on current pretax preprovision profit and the discretionary and nondiscretionary components of loan loss provisions. The model is specified as follows: $PPP_{t+1} = \alpha_0 + \alpha_1 PPP_t + \alpha_2 NDLLP_t + \alpha_3 DLLP_t + \varepsilon_\tau$ **, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.*
PPP: Preprovision profit. It is net income before taxes, loan loss provisions, and extraordinary items,, and discontinued operations..
NDLLP: Nondiscretionary loan loss provision. It is the fitted value from the respective discretionary loan loss provision model.
DLLP Discretionary loan loss provision. It is the residual from the respective discretionary loan loss provision model.

Table 4 provides the results of analyzing the persistence of discretionary and nondiscretionary loan loss provision components with respect to future loan loss provisions. The coefficients on both the nondiscretionary and discretionary components of loan loss provision are positive and highly significant for all of the models. The nondiscretionary component is expected to have a positive coefficient. However, the discretionary component should be negative if it is perfectly isolating managerial discretion. Since it is only partially isolating discretion, the coefficient on the discretionary component is a weighted average of the expected coefficients for the nondiscretionary and discretionary components.

Table 4: Loan Loss Provision Persistence Test. Results of Regressing Future Loan Loss Provisions on the Discretionary and Nondiscretionary Components of Loan Loss Provisions

Model	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	-0.0002 (-19.0)***	-0.0001 (-10.5)***	0.0006 (116.0)***	0.0006 (117.1)***	0.0006 (114.5)***
NDLLP	1.1543 (178.0)***	1.0747 (222.1)***	0.4933 (281.4)***	0.4882 (278.5)***	0.5013 (289.1)***
DLLP	0.3547 (281.7)***	0.3333 (264.3)	0.2705 (156.3)**	0.2751 (158.8)	0.2578 (147.7)
Adjusted R-squared	0.1325	0.1409	0.1247	.1239	0.1266

Table 4 shows the results of regressing future loan loss provisions on the discretionary and nondiscretionary components of loan loss provisions. The model is specified as: $LLP_{t+1} = \alpha_0 + \alpha_1 NDLLP_t + a_2 DLLP_t + \varepsilon_\tau$ *. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.*
LLP: Loan loss provisions one quarter ahead.
NDLLP: Nondiscretionary loan loss provision. It is the fitted value from the respective discretionary loan loss provision model.
DLLP Discretionary loan loss provision. It is the residual from the respective discretionary loan loss provision model.

The lower the coefficient on the discretionary component the more consistent that model is with isolating discretion. All of the models have a lower coefficient on the discretionary component. This is consistent with all of the models isolating a portion of discretionary loan loss provisions. The model introduced in this paper outperforms the extant models in this test. The coefficient on the discretionary component is 0.2578 and is the lowest of all of the models suggesting that this model produces the discretionary component with the least persistence.

Table 5 provides the final persistence test for the discretionary loan loss provision models. As mentioned earlier any managerial discretion in the current period must eventually be offset by an equal and opposite amount of managerial discretion in the future. Future values of the discretionary loan loss provision (DLLP) are regressed on current values of discretionary loan loss provisions. The coefficient on the discretionary loan loss provision in the new model is 0.0101, which is the lowest of all of the models. The new model that includes the loan type variables produces the least persistent discretionary loan loss provision component that is consistent with isolating the greatest proportion of managerial discretion.

Table 5: Persistence Test for Discretionary Loan Loss Provisions.

$$DLLP_{t+1} = \beta_0 + \beta_1 DLLP_t + \varepsilon_t$$

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	-0.0000 (-1.6)	-0.0000 (-1.1)	-0.0000 (-2.5)**	-0.0000 (-2.7)***	-0.0000 (-2.6)***
DLLP	0.3117 (270.3)***	0.2683 (229.7)***	0.0240 (20.1)***	0.0273 (22.8)***	0.0101 (8.4)***
Adjusted R-squared	0.0931	0.0690	0.0006	.0007	0.0001

*Table 5 shows the results of regressing future discretionary loan loss provisions on current discretionary loan loss provisions . *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively. DLLP is discretionary loan loss provision. It is the residual from the respective discretionary loan loss provision model.*

CONCLUDING COMMENTS

The purpose of this paper is to provide evidence on the validity of discretionary loan loss provision models. There is very little published research on this topic and the conclusions from many research studies examining managerial discretion in the banking industry rely on the ability of these models to separate loan loss provisions into discretionary and nondiscretionary components. This paper develops a new model of discretionary loan loss provisions that incorporates specific types of loans such as credit cards, real estate, commercial, and individual loans. The paper then studies the validity of the new model and four extant models from the literature. One test examines the ability of the models to predict variation in the loan loss provision. The other tests analyze the persistence characteristics of the nondiscretionary and discretionary components from each of the models. The research uses bank call report data during the period 1992 quarter 4 through 2013 quarter 3. This data is publicly available for all banks that report to the Federal Deposit Insurance Corporation (FDIC).

The new model has the highest adjusted r-squared and is therefore the best performer in predicting loan loss provisions. The addition of nonperforming credit card loans is particularly significant and its coefficient has a magnitude many times the size of other nonperforming loan categories. The discretionary component from the new model is the best performer for two of the three persistence tests and is the second best performer for the third persistence test. The results are consistent with most of the models isolating a portion of managerial discretion. Taken together, the results are consistent with the new model outperforming the other models currently used in the literature.

This study has several limitations. First, the analysis focuses on four models used by Beatty and Liao (2013) that capture the factors used in nine models from the literature. Examining the nine models directly would provide more information about the effectiveness of extant models. Since Beatty and Liao (2013) essentially include the entire set of variables used in the literature it seems likely that extant models will not perform as well. A big limitation is that researchers only have proxies for managerial discretion. Managers do not actually report their discretion. The analysis examines characteristics of discretion that are necessary for discretion to have taken place. Ideally, factors that are both necessary and sufficient to show discretion could be identified.

Future research could examine a number of issues. First, since discretionary loan loss provision models are essentially the banking parallel of discretionary accrual models and since discretionary accrual models have been tested extensively, virtually all of the tests examining the validity of these models could be applied to discretionary loan loss provision models. The power and specification of discretionary loan loss provision models could be examined as in Dechow, Sloan, and Sweeeney (1995). Reversal tests, the Vuong test, and accrual estimation error tests could also be studied. Second, additional variables could be included in developing a better discretionary loan loss provision model. Additional loan type variables could be added to the model—such as loans for sale, restructured loans, loans where interested has not yet been collected—and then all of these could be further disaggregated into real estate, credit card, commercial, industrial, government, farm, foreign, and individual loans. The loan variables could also be disaggregated geographically. Finally, the loan loss allowance account could be examined instead of the loan loss provision account. The development of a discretionary loan loss allowance model would be a new way to look at managerial discretion. The loan loss allowance account is essentially the balance sheet accumulation of unused loan loss provisions. Since it is a balance sheet account it is fundamentally more related to the loan credit quality accounts used in discretionary loan loss provision models. The discretionary and nondiscretionary components of the loan loss provision could also be derived from a discretionary loan loss allowance account.

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