Does Citizens' Financial Literacy Relate to Bank Financial Reporting Transparency?

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Abstract

In this study, we examine the relationship between financial literacy and bank financial reporting transparency for a sample of banks from the U.S. Following prior literature, we employ discretionary loan loss provisions (DLLP) as our primary measure of bank reporting transparency. We argue that the financial literacy of their customers can influence bank managers' behaviors with respect to both the mechanics of the loan loss provisioning and their opportunistic actions. Financially literate customers represent more stable sources of funding and have more predictable loan loss provisioning that contributes to more persistent earnings. Financial literacy could also enhance customers' ability to indirectly follow and monitor bank performance and risk-taking. Therefore, bank managers will be less likely to engage in opportunistic earnings manipulation. Following these arguments, we predict that citizens' financial literacy is positively associated with bank financial reporting transparency. Consistent with our prediction, we find that the magnitude of bank DLLP is negatively related to state-level financial literacy. Moreover, the association between financial literacy and DLLP is higher for banks with more retail deposits and larger consumer loans, the two channels through which financial literacy could influence bank transparency.

Keywords: Financial Literacy; Financial Reporting Transparency; Loan Loss Provisions; Earnings Quality

1. Introduction

The global financial crisis following the 2007 subprime meltdown stimulated governments' interest in improving their citizens' financial literacy. The Organization for Economic Cooperation and Development (OECD, 2013, p. 144) defines financial literacy as the 'knowledge and understanding of financial concepts and risks, and the skills, motivation and confidence to apply such knowledge and understanding in order to make effective decisions across a range of financial contexts, to improve the financial well-being of individuals and society.' The rising interest in financial literacy stems from increased individual responsibility (due to factors such as longer life expectancy, higher costs of education, and reductions in state-supported pensions and healthcare benefits) and an increased supply of, and demand for, financial products and services (OECD, 2013). In addition, a lack of financial literacy contributes to poor financial decisionmaking, which could have devastating consequences, such as personal bankruptcy and market collapse. Consequently, financial literacy is now recognized as an essential element of the policy mix for financial stability. However, OECD (2018) has emphasized that financial education can change the behavior of individuals, but it may not be significant enough to have macro-level implications. Therefore, in this research, we examine one of the broader economic implications of financial literacy: the relationship between citizens' financial literacy and financial reporting practices in the banking industry.

We argue that financial literacy can influence bank transparency through retail deposits and consumer loans. In particular, retail deposits from financially literate customers are a more stable source of funding for banks. For example, Kim (2015) observes that financially literate depositors make fewer withdrawals after banks receive an enforcement action, implying that financial literacy can mitigate cognitive biases in depositor behavior during bank runs. Customers obtain loans from banks, including mortgages, auto loans, student loans, and credit cards, for individual or family needs. We argue that the expected losses of loans made to financially literate customers tend to be smaller and more predictable, as they have more definitive plans for borrowing and repayment than the expected losses on loans made to less financially literate customers. Lusardi and Tufano (2015) find that individuals who are financially illiterate tend to take on excessive amounts of debt or are unsure of the appropriateness of their debt position. Therefore, when loans are made to financially literate borrowers, the losses are lower and are more predictable. Consequently, banks will experience fewer abnormal delinquencies and lower earnings uncertainty. Additionally, financial literacy could also enhance customers' ability to indirectly follow and monitor bank performance and risk-taking. Financially literate customers are more likely to read and understand financial news and analyst reports, which may disclose additional information. Therefore, bank managers will be less likely to engage in opportunistic earnings manipulation.

To test our hypothesis, we use a sample that includes 744 individual U.S. banks with 4,825 bank-year observations, covering the post-crisis period of 2009–2019. We obtain banks' financial data from the Compustat Bank Database and financial literacy data from the 2009, 2012, 2015, and 2018 National Financial Capability Study (NFCS) State-by-State Surveys, each of which consists of nationwide online surveys of more than 25,000 American adults (<u>https://www.usfinancialcapability.org</u>).¹ In measuring the financial literacy of Americans in each state, the surveys in Appendix A include five questions about financial concepts to test

¹ The NFCS data have been widely used by prior economics and business literature on the topic of financial literacy. Using data collected by the NFCS in 2009, Babiarz and Robb (2014) investigate the relationships between measures of financial knowledge and the probability of having enough savings to cover three months of typical expenses. Using 2012 NFCS surveys, Kim and Lee (2018) investigate the relationship between financial literacy and payday loan use. Kim et al. (2019) study financial literacy on mortgage repayment delinquency using the 2015 NFCS dataset.

respondents' understanding of the interest rate, inflation, risk diversification, bond, and mortgage. We construct the index of statewide financial literacy (*FINLIT*) by calculating the average ratio of correct responses to the five financial literacy questions for each state for the years 2009, 2012, 2015, and 2018. Finally, we use multiple imputations to fill in the missing data for the years 2010 to 2011, 2013 to 2014, and 2016 to 2017.²

We use the magnitude of discretionary loan loss provision (*DLLP*) as our primary measure of bank transparency. Prior literature has employed *DLLP* as a measure of earnings quality. For example, Kanagaretnam et al. (2010) document that auditor-fee dependence is associated with earnings management via *DLLP*. Beatty and Liao (2014) find that banks with a greater magnitude of *DLLP* tend to file more earnings restatements. Our empirical tests show that the financial literacy index *FINLIT* is negatively and significantly associated with the absolute value of *DLLP* (*ABSDLLP*). In terms of economic significance, a one-standard deviation increase in *FINLIT* is associated with a 13.5% decrease in Kanagaretnam et al.'s (2010) measure of *ABSDLLP* and a 16.2% decrease in Beatty and Liao's (2014) measure of *ABSDLLP*. These results suggest that citizens' financial literacy negatively influences bank managers' discretion to manage earnings. The results remain robust when we employ statewide postsecondary education status as our instrumental variable in a two-stage least squares (2SLS) regression analysis to mitigate potential endogeneity concerns. Our results also remain robust to the exclusion of banks with potential M&A activities and various alternative measures of

² Multiple imputation is a simulation-based statistical technique for handling missing data. Kofman and Sharpe (2003) suggest using multiple imputation in the analysis of incomplete observations in finance. To predict the missing values of *FINLIT*, a linear regression imputation method (i.e., regressing *FINLIT* on *EDUC*, *INCOME*, *GENDER*, *MARIT*, *RACE*, and state fixed effects) is used. This process of fill-in is repeated multiple times using Monte Carlo simulation by averaging each of these separate analyses. *EDUC* is the statewide proportion of the population receiving post-secondary education, *INCOME* is the natural logarithm of statewide per capita income, *GENDER* is the statewide proportion of the male population, *MARIT* is the statewide proportion of the married population, *RACE* is the statewide proportion of the white race. Prior literature documents that education level, marital status, income, and sex are associated with financial literacy (Lusardi & Mitchell, 2011a, 2011b, 2011c).

ABSDLLP, including *FINLIT* in the estimation of *DLLP*, and employing signed *DLLP*. Collectively, our results indicate that financial literacy is positively related to the financial reporting transparency of banks.

Next, we examine the influence of retail deposits and the level of consumer loans, the two specific channels through which financial literacy could influence bank transparency. We find that, when banks have more retail deposits, the attenuating effect of financial literacy on *ABSDLLP* is more pronounced. The results suggest that, with retail deposits, financial literacy can translate into higher bank transparency. Similarly, we document that the moderating effect of financial literacy on *ABSDLLP* is more pronounced with higher levels of consumer loans. This is consistent with financially literate borrowers having more predictable loan losses that contribute to less estimation errors in loan loss provisioning.

Our study makes three important contributions. The first contribution is that we direct the financial literacy research from individual and household behaviors to the practices of the banking sector. Arguably, citizens' financial literacy can support financial and economic stability by strengthening societal resilience to major financial shocks, such as the subprime meltdown (OECD, 2018). However, empirical evidence on how this process manifests itself is sparse. For example, the literature is unclear on the influence of financial literacy on the banking industry. Our research indicates that bank earnings quality improves as banks have a larger base of financially literate customers.

The second contribution is that our study provides initial evidence in line with the rising interests in financial literacy policies. Since the 2007–2008 financial crisis, governments have emphasized financial literacy in supporting inclusive and sustainable growth. For instance, on July 15, 2019, the U.S. Department of the Treasury released a report titled 'Federal Financial

Literacy Reform: Coordinating and Improving Financial Literacy Efforts,' which highlights the importance of financial literacy for Americans, identifies ways to deliver financial education effectively and efficiently, and recommends federal action to improve financial capability for consumers and communities. If citizens' financial literacy improves following federal initiatives, their financial behaviors should become more stable and predictable, as suggested by our findings.

Finally, our paper contributes to the literature on understanding the accruals process of loan loss provisioning. Although prior research documents that earnings variability and estimation errors matter for loan loss provisioning, our results provide insight into how this accruals process is influenced by different underlying customer pools. Moreover, our research is also related to the determinants of loan loss provisions. Prior literature documents that regulation, culture, social capital, and policy uncertainty, among other factors, play an important role in determining bank loan loss provisions (e.g., Fonseca & Gonzalez, 2008; Kanagaretnam et al., 2011; Jin et al., 2019; Ng et al., 2020). As a supplemental contribution to prior literature, our paper finds that citizens' financial literacy is an important factor that influences loan loss provisions and bank earnings quality.

The rest of this paper is organized as follows. Section 2 reviews the literature and develops our hypotheses on the relationship between financial literacy and bank accounting discretion. Section 3 describes our data and research design. Section 4 presents our empirical results, and Section 5 reports the results of additional analyses. Section 6 discusses robustness checks, and Section 7 concludes our paper.

2. Literature Review and Hypotheses Development

The literature on financial literacy has focused mainly on the relationships between financial literacy and positive behavioral changes in individuals and households. Research shows that individuals who are financially literate are more likely to save and plan for retirement (Cole et al., 2011; Lusardi & Mitchell, 2011a, 2011b) and to accumulate greater wealth (Stango & Zinman, 2009). Calvet et al. (2009) document that financially educated households are less prone to making financial mistakes than other households. Hastings and Tejeda-Ashton (2008) find that individuals who are financially literate are much more likely to choose mutual funds with lower fees; Van Rooij et al. (2011) find that the financially literate are more active investors in the stock market and have better-performing portfolios. Hisao and Tsai (2018) demonstrate that financial literacy brings a significant benefit to individuals by lowering their entry barriers to the purchase of complex derivative products such as options. Financial literacy also has implications for borrowing and choice of debt. Gerardi et al. (2013) show that, during the 2008 financial crisis, individuals with limited financial knowledge and numerical ability were more likely to default on subprime mortgages. According to Lusardi and Tufano (2015), individuals who are less financially literate tend to incur higher fees and take out higher-interest loans.

Bank financial reporting is important for regulatory and investment purposes. Barth and Landsman (2010) argue that bank regulators use the information supplied in bank financial statements as inputs to calculate regulatory capital measures and enhance financial stability. In addition, shareholders/investors may rely on banks' financial information to trade banks' stocks. On the other hand, opacity in bank reporting aids bank managers' expropriation of resources for self-interest. For example, bank managers may increase provisions in good years and decrease them in bad years to smooth income and mask the underlying riskiness. We argue that the financial literacy of their customers can influence bank managers' behaviors with respect to both the mechanics of the accrual process and their opportunistic actions.³ On the one hand, the mechanics of the accrual process are improved with fewer estimation errors and low variability. Because financially literate depositors are less likely to panic during times of uncertainty (Kim 2015), they represent more stable funding, through which banks can generate more persistent earnings. In addition, the borrowing and repayment behaviors of financially literate borrowers are typically more predictable, and the low variation in risk will reduce provisioning and accruals errors for banks (Lusardi & Tufano, 2015).

On the other hand, to the extent that financially literate depositors could be involved in monitoring banks' financial reporting process and risk-taking, bank managers will be less likely to engage in opportunistic earnings manipulation. Scandals about bank underperformance and risk often lead to media coverage. Financially literate customers are more likely to read and understand financial news and analyst reports, which may disclose additional information. Thus, financially literate individuals can take corresponding actions (e.g., withdraw their deposits) and exercise their monitoring function on banks even if they may not directly read bank financial statements per se to access bank financial condition. Taken together, our hypothesis on the relationship between citizens' financial literacy and bank financial reporting transparency is as follows:

H1: Citizens' financial literacy is positively associated with bank financial reporting transparency.

In developing the above hypothesis, we relied on the argument that retail deposits and consumer loans are two important channels through which the financial literacy of retail

³ Although FASB has required the use of the incurred-loss model for loan loss provisioning (up to December 15, 2019), the complexity of loan portfolios allows a substantial magnitude of discretion within the prescribed rules (Dugan, 2009).

depositors and borrowers of consumer loans may relate to bank transparency. Retail deposits from financially literate customers are a more stable source of funding for banks. For example, Kim (2015) provides evidence that financial literacy mitigates biases in depositor behavior during bank runs following the issuance of FDIC enforcement actions. He finds that the financial literacy of respondents in nearby branches of banks receiving an enforcement action significantly reduces deposit outflows. When banks have greater funding stability to generate persistent earnings and cash flows, there are fewer incentives for them to engage in earnings management.

Conversely, Maechler and McDill (2006) argue that depositors can monitor banks for poor performance or excessive risk-taking by reducing deposits or demanding a higher risk premium. An extreme form of monitoring by depositors can even lead to bank runs. We argue that, although retail depositors may not directly monitor bank financial performance by going through bank financial statements per se, financially literate depositors could be more likely to search for financial news, which may disclose certain information about their banks. As such, depositors can take corresponding actions by either withdrawing their deposits from banks or demanding higher deposit rates.

At the same time, banks extend personal credit in the form of consumer loans for personal or family use. These loans include mortgages, auto loans, student loans, and credit cards. We argue that the expected losses of loans borrowed by financially literate customers tend to be more predictable, as they have more definitive plans for borrowing and repayment. When loans are made to financially literate borrowers, the deviation of delinquency from expected loan losses is smaller, meaning banks will experience fewer abnormal loan losses and therefore exhibit higher earnings transparency.⁴

In our context, when exposed to higher retail deposits and consumer loans, banks will interact more with retail depositors and individual loan borrowers; thus, bank behaviors will be more subject to the influence of these customers. Therefore, we would expect greater bank earnings transparency when banks have more retail deposits and higher consumer loans from financially literate customers. Thus, our second and third hypotheses are as follows:

H2: The association of financial literacy with bank financial reporting transparency is stronger when banks have more retail deposits.

H3: The association of financial literacy with bank financial reporting transparency is stronger when banks have more consumer loans.

3. Data and Research Design

To test our hypotheses, we gather data on bank financial information and citizens' financial literacy. We obtain bank-level data from the Bank Compustat Database. As the proxy for financial literacy, we use the annual statewide financial literacy index constructed from the NFCS surveys. A higher value of *FINLIT* indicates customers who are more financially literate. Our financial literacy data come from the 2009, 2012, 2015, and 2018 National Financial

⁴ It seems that the extent of managerial discretion over loan loss provisions is low for consumer loans to begin with, as bank regulators have requirements for the timeline over which consumer loans are charged off, suggesting that the provisioning could also be mechanical. This is consistent with prior research arguing that banks have more discretion over commercial loans compared to consumer loans (e.g., Liu & Ryan, 2006). However, the Federal Reserve Bank of Kansas City (2018) emphasizes the allowance of discretion with pricing or underwriting decisions for consumer loans. Frequently observed discretionary pricing practices include lack of established rate sheets, reliance on unwritten pricing guidelines, reliance on vague and/or unwritten discretionary criteria when making adjustments to established rate sheets (e.g., good customer, large depositor), lack of guidance to select a rate from an established rate range, and inadvertent omission of pricing guidelines for certain credit requests. Therefore, the Fed advocates a compliance management system that includes an evaluation of the bank's discretionary practices to determine the level of fair lending risk posed by such practices, as well as the controls in place to properly identify, measure, control, and monitor risks.

Capability Study (NFCS) State-by-State Surveys, which were nationwide online surveys of more than 25,000 American adults (https://www.usfinancialcapability.org). The research objectives of the NFCS are to benchmark key indicators of financial capability and evaluate how these indicators vary with underlying demographic, behavioral, attitudinal, and financial literacy characteristics. The NFCS data have been widely used by prior economics and business studies on financial literacy. For example, Kim and Lee (2018) investigate the relationship between financial literacy and the use of payday loans. Kim et al. (2020) study financial literacy in relation to mortgage repayment delinquency using the 2015 NFCS dataset. In measuring financial knowledge, the surveys include five financial literacy questions (please see Appendix A) to gauge respondents' knowledge of these terms: interest rate, inflation, risk diversification, bond, and mortgage. For each state, we calculate the average ratio of correct responses to each of these five questions for the years 2009, 2012, 2015, and 2018. Then we use multiple imputations to fill in the years 2010 to 2011, 2013 to 2014, and 2016 to 2017 to construct annual statewide citizens' financial literacy indices.⁵

Bank reporting transparency derives from how closely a bank's true underlying fundamentals map into reported accounting numbers (Bushman, 2016). Following prior literature (e.g., Jiang et al., 2016), we focus on loan loss provisions because loan loss provisioning is an important accounting policy choice that directly influences the volatility of bank earnings, as well as the information properties of banks' financial reports reflecting the risk attributes of loan

⁵ As an alternate proxy for financial literacy, we calculate the financial literacy score (*FINLITW*) for each multi-state bank by using the weighted average *FINLIT* based on state-level deposits (aggregated from branch-level data available from FDIC's Summary of Deposits). We re-estimate all our regression models using *FINLITW*, and the untabulated results show that *ABSDLLP_A* and *ABSDLLP_B* are significantly and negatively associated with *FINLITW* at the 1% level.

portfolios (Bushman, 2016). To measure bank accounting discretion, we focus on the magnitude of DLLP, through which banks can manipulate both earnings and regulatory capital. Loan loss provision (LLP) is an expense item for banks, representing banks' current estimates of future losses from defaults on outstanding loans (Cohen et al., 2014). LLP is the largest accrual in bank accounting, thereby affording bank managers wide latitude for potential manipulation (Beatty & Liao, 2014). There are three important ways to manipulate DLLP to reduce earnings quality. First, banks can smooth their earnings by decreasing DLLP when income is too low and increasing *DLLP* when income is too high (Fonseca & Gonzalez, 2008). Second, bank managers can manage banks' regulatory capital through *DLLP*. Banks with low regulatory capital may intentionally decrease their LLP because each one-dollar decrease in LLP increases Tier 1 capital by one dollar times (1-tax rate) given the loan loss allowance is not added back to Tier 1 capital (Beatty & Liao, 2014). Third, *DLLP* can reflect the timely recognition of expected future loan losses (Bushman & Williams, 2012). DLLP measures the extent to which banks deviate from their normal LLP level to manage earnings; therefore, it is widely used in prior studies as a measure of bank transparency. For example, Kanagaretnam et al. (2010) find that auditor fee dependence is associated with earnings management via DLLP. Beatty and Liao (2014) find that banks with a greater magnitude of DLLP tend to file more earnings restatements and receive more comment letters from the U.S. Securities and Exchange Commission (SEC).

We proxy for *DLLP* as the residual from the regression of *LLP* using Model (1a), which is a modified version of Kanagaretnam et al.'s (2010) model.^{6,7} The residual captures a bank's deviation from the normal level of *LLP*, thereby measuring *DLLP*.

⁶ As *FINLIT* is a state-level variable, this test raises the concern that state-level economic factors can affect both financial literacy and bank loan loss provisioning. To account for the different economic conditions, we compute *ABSDLLP* by estimating the first-stage model by state-year to allow the coefficients of the determinants to vary. In a

$$LLP_{it} = \alpha_0 + \alpha_1 LLA_{it-1} + \alpha_2 NPL_{it-1} + \alpha_3 LOAN_{it} + \alpha_4 \Delta LOAN_{it} + \alpha_5 CHO_{it} + \alpha_6 \Delta NPL_{it} + \alpha_7 \Delta GDP_{it} + \alpha_8 \Delta UNEMP_{it} + \alpha_9 \Delta HPI_{it} + YEAR_FIXED_EFFECTS + \varepsilon_{it}$$
(1a)

where *LLP* is loan loss provision divided by lagged total loans; *LLA* is loan loss allowance divided by total loans; *NPL* is nonperforming loans divided by lagged total loans; *LOAN* is total loans divided by total assets; $\Delta LOAN$ is change in total loans divided by lagged total loans; *CHO* is loan charge-offs divided by lagged total loans; ΔNPL is change in nonperforming loans divided by lagged total loans; ΔGDP is change in state GDP over the year; $\Delta UNEMP$ is change in the state unemployment rate over the year; and ΔHPI is the change in the state house price index over the year. We include lagged *LLA* to account for the fact that banks previously allowing for higher expected loan losses will typically recognize less provision in the current year. *CHO* is included because loan charge-offs influence the expectation of collecting current loans and, hence, current *LLP*. We also include the loan growth rate because fast-growing loans might be associated with a decrease in loan quality. *YEAR_FIXED_EFFECTS* are year dummy variables to account for year fixed effects.

To confirm that our test results are not driven by choice of a specific loan loss provision estimation model, we employ an alternative specification used by Beatty and Liao (2014) to estimate *DLLP*. As before, we measure *DLLP* using the residual term of Model (1b).

robustness test, the second-stage model shows that *FINLIT* is significantly and negatively associated with *ABSDLLP* computed at the state-year level.

⁷ Bhat et al. (2019) identify that commonly used measures of LLP timeliness vary substantially across loan types. We examine the relationship between financial literacy and bank loan types, including consumer loans, real estate loans, and commercial loans studied by Bhat et al. (2019). The untabulated results show that the financial literacy of bank customers is significantly and negatively associated with consumer loans and real estate loans, but not commercial loans. This is consistent with prior literature documenting that financially literate consumers are less likely to take excessive amounts of debt (Lusardi & Tufano, 2015). In a robustness test, we incorporate bank loan types in the first-stage *LLP* estimation model. The untabulated results for the second-stage model show that *ABSDLLP* has a significantly negative relationship with *FINLIT* even after controlling for consumer loans, real estate loans, and commercial loans.

 $LLP_{it} = \alpha_0 + \alpha_1 \Delta LOAN_{it} + \alpha_2 CHO_{it} + \alpha_3 \Delta NPL_{it} + \alpha_4 \Delta NPL_{it+1} + \alpha_5 \Delta NPL_{it-1} + \alpha_6 \Delta NPL_{it-2} + \alpha_7 SIZE_{it-1} + \alpha_8 \Delta GDP_{it} + \alpha_9 \Delta UNEMP_{it} + \alpha_{10} \Delta HPI_{it} + YEAR_FIXED_EFFECTS + \varepsilon_{it}$ (1b)

where *SIZE* is the natural logarithm of total assets. This model allows for changes in nonperforming loans in consecutive periods ΔNPL_{it} , ΔNPL_{it+1} , ΔNPL_{it-1} , and ΔNPL_{it-2} , as banks might use current, future, and historical information on nonperforming loans to select *LLP*. The model also includes bank size (*SIZE*) because official supervisory oversight could vary with bank size. Basu et al. (2020) suggest that loan charge-offs should also be included in the linear model of *LLP* after comparing four potential models proposed by Beatty and Liao (2014). They find that loan charge-offs are associated with declines in nonperforming loans and increases in *LLP*, inducing a V-shaped relationship between *LLP* and change in nonperforming loans. They indicate that 'failure to model the asymmetry attributable to loan charge-offs can change inferences about the presence of earnings management and the effects of delayed loan loss recognition in prior papers that assumed linearity.' Thus, we control for loan charge-offs (*CHO*) in the first-stage *LLP* estimation model.⁸

We use the absolute value of *DLLP* estimated from Models (1a) and (1b), *ABSDLLP_A* and *ABSDLLP_B*, as our main proxies for bank accounting discretion. Higher values of *ABSDLLP_A* and *ABSDLLP_B* indicate greater accounting discretion and lower transparency. To test the influence of citizens' financial literacy on financial reporting transparency, we estimate the following regression models.

$$ABSDLLP_{it} = \alpha_{it} + \alpha_1 FINLIT_t + \alpha_2 V_{it} + \alpha_3 W_t + BANK_FIXED_EFFECTS + YEAR_FIXED_EFFECTS + \varepsilon_{it}$$
(2)

⁸ We also follow Beatty and Liao (2014) to exclude loan charge-offs in the first-stage *LLP* estimation Model (1b). The untabulated results of the second-stage regression remain robust after we exclude loan charge-offs in Model (1b).

ABSDLLP is either ABSDLLP A or ABSDLLP B. Our primary variable of interest is the statewide citizens' financial literacy index, FINLIT, computed from the NFCS Surveys. Based on our expectation that customers' financial literacy reduces average bank reporting discretion, we predict FINLIT to be negatively and significantly associated with ABSDLLP A and ABSDLLP B. V is an array of financial variables to control for bank characteristics that vary with time. Following Jiang et al. (2016) and Jin et al. (2019), we include bank size (SIZE), capital ratio (CAPR), earnings before loan loss provisions (EBP), and assets growth rate (ASG).⁹ We control for bank risk, which is measured by Z-score (ZSCORE) as defined by Kanagaretnam et al. (2014). Z-score is a measure of bank stability that indicates the distance from insolvency (Laeven and Levine 2009). We calculate ZSCORE as the natural logarithm of $(EBP + CAPR)/\sigma(EBP)$, where *EBP* is the mean of earnings before loan loss provisions divided by total assets over the sample period; CAPR is the mean of total equity divided by total assets over the sample period, and $\sigma(EBP)$ is the standard deviation of EBP over the sample period. We multiply the score by -1 so that a higher ZSCORE implies more risk. W is an array of state characteristics, including change in per capita GDP (ΔGDP), change in the unemployment rate ($\Delta UNEMP$), and change in the house price index (ΔHPI). In addition, we control for bank fixed effects and year fixed effects. As before, to account for the possibility that the error terms might be correlated, we cluster the standard errors at the state level.

To test H2 and H3 on the influence of retail deposits (*DEPOSIT*) and consumer loans (*CLOAN*), we interact them with *FINLIT* and include the interaction terms in Models (3) and (4), respectively.

⁹ To empirically control for income smoothing, we include the variable *EBP* (earnings before loan loss provisions divided by total assets) in our second stage of *ABSDLLP* regressions to account for the fact that management may manipulate *LLP* to achieve its desired level of net income.

 $ABSDLLP_{it} = \alpha_{it} + \alpha_1 FINLIT_t + \alpha_2 DEPOSIT_{it} + \alpha_3 FINLIT_t * DEPOSIT_{it} + \alpha_4 V_{it} + \alpha_5 W_t + BANK_FIXED_EFFECTS + YEAR_FIXED_EFFECTS + \varepsilon_{it}$ (3)

$$ABSDLLP_{it} = \alpha_{it} + \alpha_1 FINLIT_t + \alpha_2 CLOAN_{it} + \alpha_3 FINLIT_t * CLOAN_{it} + \alpha_4 V_{it} + \alpha_5 W_t + BANK_FIXED_EFFECTS + YEAR_FIXED_EFFECTS + \varepsilon_{it}$$
(4)

where *DEPOSIT* is defined as the decile rank of retail deposits, and *CLOAN* is defined as the decile rank of consumer loans.¹⁰ *ABSDLLP*, *FINLIT*, *V*, and *W* are defined in the same way as in Model (2). To the extent that the influence of financial literacy on earnings quality is greater for banks with more exposure to retail deposits and consumer loans, we would expect the interaction terms *FINLIT*DEPOSIT* and *FINLIT*CLOAN* to be negatively and significantly associated with *ABSDLLP*.

4. Empirical Results

We present the descriptive statistics for the variables used in the regressions in Table 1. After deleting observations with insufficient data, we have a total of 744 unique U.S. banks with 4,788 bank-year observations covering the post-financial crisis period from 2009 to 2019. During the sample period, the mean values of *ABSDLLP_A* and *ABSDLLP_B* are both 0.002, while the median values are 0.001. In comparison, the mean and median values of *LLP* are 0.006 and 0.003, respectively. The financial literacy variable *FINLIT* has a mean value of 0.596 and a median value of 0.592, suggesting that the average correct response to financial concept questions by U.S. adults is about 60%. As for the control variables, we find that the average capital ratio (*CAPR*) of U.S. banks is 10.4% and the average asset growth rate (*ASG*) is about

¹⁰ As Hirshleifer et al. (2009) suggest, the decile rank has the advantage of reducing the influence of outliers. It also helps to linearize the relationship between *ABSDLLP* and *FINLIT*. We calculate *DEPOSIT* as the decile rank of the sum of RCON3485, RCONB563, RCON3486, RCON3487, RCONA529, and RCON3469 scaled by RCFD2170 (from Call Reports) or the sum of DPDC, CTTD, DPSC, and MMCD scaled by AT (from Compustat Bank database) if Call Reports data are missing. Similarly, we calculate *CLOAN* as the decile rank of RCFD1975 scaled by RCON2122 (from Call Reports) or LCACRD scaled by LNTAL (from Compustat Bank database) if Call Reports data are missing.

7.6%. Descriptive statistics also show that the U.S. experienced a growth in GDP, a decline in the unemployment rate, and an increase in housing prices during the sample period.

[Table 1 near here]

We report the Pearson correlations of the variables in Table 2. *FINLIT* is significantly and negatively correlated with *ABSDLLP_A* and *ABSDLLP_B* at the 1% level, indicating that statewide financial literacy is associated with less accounting discretion via *DLLP*. Moreover, we find that *ABSDLLP_A* and *ABSDLLP_B* are significantly correlated with each other and with all other selected variables at the 1% level.

[Table 2 near here]

We present the OLS regression results of *DLLP* estimation in Table 3, with Column 1 displaying Kanagaretnam et al.'s (2010) model and Column 2 showing Beatty and Liao's (2014) model. Most of the estimated coefficients are consistent with those reported by previous studies (e.g., Kanagaretnam et al., 2010; Beatty & Liao, 2014; Bushman et al., 2015). Column 1 shows that LLA_{it-1} is significantly and negatively associated with LLP_{it} at the 1% level (t-value = - 11.50), consistent with the argument that banks recognize less *LLP* in the current period if they have already had a high beginning loan loss allowance. $LOAN_{it}$ is significantly and positively associated with LLP_{it} at the 5% level (t-value = 2.23), meaning that a larger amount of loans will also require a higher level of loan loss provisions. CHO_{it} is also significantly and positively associated with LLP_{it} at the 1% level (t-value = 48.40), consistent with the argument that current loan charge-offs can influence expectations of the collectability of current loans and, thus, current *LLP* (Beaver & Engel, 1996). In addition, ΔNPL_{it} has a positive and significant relationship with LLP_{it} at the 1% level (t-value = 8.57), implying that an increase in nonperforming loans requires more *LLP* in the current period. Column 2 reports positive and

significant coefficients for ΔNPL_{it} , ΔNPL_{it+1} , ΔNPL_{it-1} , and ΔNPL_{it-2} , suggesting that banks incorporate both current, future, and past information on the change in nonperforming loans to estimate *LLP*. $\Delta LOAN_{it}$ has a positive and significant coefficient at the 1% level (t-value = 4.70), indicating that the estimation of *LLP* depends on the quality of incremental loans. The absolute values of the residuals from Models (1) and (2) are denoted as *ABSDLLP_A* and *ABSDLLP_B*, respectively, and are our main proxies for bank reporting transparency.

[Table 3 near here]

We report the univariate comparisons of *ABSDLLP_A* and *ABSDLLP_B* between high and low *FINLIT* states in Table 4. The mean values of *ABSDLLP_A* and *ABSDLLP_B* are 0.0021 and 0.0022 for banks in below-median *FINLIT* states, which are higher than the mean value of 0.0018 for banks in above-median *FINLIT* states. The difference is statistically significant at the 1% level. Similar patterns can also be seen in the median values of *ABSDLLP_A* and *ABSDLLP_B*, with banks in low *FINLIT* states reporting significantly more discretionary loan loss provision than their peers in high *FINLIT* states.

[Table 4 near here]

Table 5 presents the baseline OLS multivariate regression results for testing Hypothesis 1 on the relationship between financial literacy and discretionary loan loss provision. After controlling for state and year fixed effects, we find that *FINLIT* is negatively and significantly related with *ABSDLLP_A* and *ABSDLLP_B* at the 1% level (*t*-value = -4.66 and -5.73, respectively) in Columns 1 and 2. After controlling for bank and year fixed effects, we find that *FINLIT* is negatively and significantly related with *ABSDLLP B* at the 1% level (*t*-value = -4.66 and -5.73, respectively) in Columns 1 and 2. After controlling for bank and year fixed effects, we find that *FINLIT* is negatively and significantly related with *ABSDLLP A* and *ABSDLLP B* at the 1%

level (*t*-value = -5.72 and -6.21, respectively) in Columns 3 and 4.¹¹ In terms of economic significance, a one standard deviation increase in *FINLIT* is associated with a 13.5% decrease in *ABSDLLP_A*. Specifically, this impact is computed as -0.010 (the coefficient of *FINLIT* in Column 1 of Table 5) × 0.027 (the sample standard deviation of *FINLIT* in Table 1) ÷ 0.002 (the sample mean of *ABSDLLP_A* in Table 1) × 100%. Meanwhile, a one standard deviation increase in *FINLIT* is associated with a 16.2% decrease in *ABSDLLP_B*. These results support our hypothesis that financial literacy is associated with less accounting discretion. As for the control variables, we find that *ABSDLLP* is significantly and negatively associated with *EBP* and ΔHPI , indicating that banks engage in less accruals manipulation in times of high earnings and high housing price growth.

[Table 5 near here]

Although we have accounted for a variety of control variables in the baseline OLS regressions, our model specification may still suffer from endogeneity issues due to unobservable characteristics. To mitigate the endogeneity concerns, we employ the two-stage least squares (2SLS) instrumental variable approach to verify the robustness of our baseline results.

Prior literature notes that personal financial literacy is influenced by educational attainment (Lusardi & Mitchell, 2011b, 2011c; Stolper & Walter, 2017). For example, Lusardi and Mitchell (2011b) find that in the U.S. 63% of respondents with at least a college degree can correctly answer basic questions about financial literacy, but only 12.6% of respondents without a college degree can. We argue that the education level of the NSCF survey takers can be viewed

¹¹ We control for bank fixed effects because many unobservable bank characteristics may affect banks' discretion on *LLP*. *LLP* discretion is sticky within a bank, and *FINLIT* is likely to be sticky over time. Therefore, we run two separate regressions: (1) including only state and year fixed effects to control for within-state variation and (2) including bank and year fixed effects to control for within-bank variation.

as an exogenous variable, given that this educational attainment must have been accumulated over a longer period preceding the survey. Furthermore, Lusardi et al. (2010) find that educational attainment is a relevant factor even after controlling for cognitive abilities. Following this line of reasoning, we use educational attainment as our instrumental variable for financial literacy. In other words, education is represented by the NFCS survey respondents' college status, a dummy variable set at 1 if the survey respondent is at least a college graduate, and 0 otherwise (data source: 2009, 2012, 2015, and 2018 NFCS State-by-State Surveys). We then use *COLLEGE* to represent the average value of the NFCS survey respondents' college status dummy variable for each state-year. We expect *COLLEGE* to have a positive and significant relationship with *FINLIT* in Model (5). The control variables in Model (5) are an array of state-level variables together with state and year fixed effects.

$$FINLIT_{t} = \alpha_{0} + \alpha_{1}COLLEGE_{t} + \alpha_{2}SIZE_{t} + \alpha_{3}CAPR_{t} + \alpha_{4}EBP_{t} + \alpha_{5}ASG_{t} + \alpha_{6}ZSCORE_{t} + \alpha_{7}\Delta GDP_{t} + \alpha_{8}\Delta UNEMP_{t} + \alpha_{9}\Delta HPI_{t} + STATE_FIXED_EFFECTS + YEAR_FIXED_EFFECTS + \varepsilon_{it}$$
(5)

where *COLLEGE* is the proportion of the population receiving post-secondary education of each state, *SIZE* is the natural logarithm of total assets, *CAPR* is the total equity divided by total assets, *EBP* is the earnings before LLP divided by assets, *ASG* is the change in assets divided by lagged assets, and *ZSCORE* is the natural logarithm of *(EBP + CAPR)/\sigma(EBP)* multiplied by -1. The remaining variables are defined in Appendix B.

We estimate the first-stage regression using Model (5) to predict the value of *FINLIT*, and use the predicted value of *FINLIT* from the first stage to test the relationship between citizens' financial literacy levels and bank accounting discretion in the second stage in Model (6). $ABSDLLP_{it} = \alpha_{it} + \alpha_1 PRE_FINLIT_t + \alpha_2 V_{it} + \alpha_3 W_t + BANK_FIXED_EFFECTS + YEAR_FIXED_EFFECTS + \varepsilon_{it}$ (6)

where *PRE FINLIT* is the predicted value of *FINLIT* from Model (5).

We report the 2SLS instrumental variable regression results in Table 6. Panel A tabulates the results for the first-stage regression using Model (5). Panel B tabulates the results for the second-stage regression using Models (4a) and (4b). In the first-stage regression, we find that *COLLEGE* is significantly and positively associated with *FINLIT* at the 1% level (t-value = 3.20), implying that individuals who have received at least a college education are more financially literate than individuals without a college education. The F-statistic is 15.828 at the 1% level, rejecting the null hypothesis that *COLLEGE* is a weak instrument for *FINLIT*. In the second stage, we find that *PRE_FINLIT*, the predicted value of *FINLIT*, is negatively and significantly correlated with *ABSDLLP_A* and *ABSDLLP_B* at the 1% level (t-value = -6.57 and -6.94, respectively). The 2SLS instrumental variable analysis supports our baseline regression results that citizens' financial literacy constrains bank accounting discretion.

[Table 6 near here]

In Hypotheses 2 and 3, we conjecture that retail deposits and consumer loans are two potential channels through which citizens' financial literacy could influence bank accounting discretion. When a bank has a larger depositor base that possesses more advanced financial knowledge, its stability of cash flows will be enhanced, and the scrutiny it receives from its customers will be more intense. We report our test results for the retail deposits channel in Table 7. We find that the coefficient of *FINLIT*DEPOSIT* is negative and significant at the 1% and 5% level (*t*-value = -3.16 and -2.24, respectively), suggesting that financial literacy has a greater influence on bank accounting discretion when banks have more deposit funding. This result supports our argument that financial literacy relates to bank earning quality through retail deposits.

[Table 7 near here]

Moreover, financially literate customers tend to have more definitive plans for their bank borrowings and repayments, so their abnormal delinquency is smaller, resulting in fewer loan defaults. We report the results of this test on consumer loans channel in Table 8. As predicted, the coefficient of *FINLIT*CLOAN* is significantly negative at the 1% and 5% levels (t-value = -2.96 and -2.34, respectively), implying financial literacy has a greater influence on bank transparency when banks have a larger exposure to consumer loans.

[Table 8 near here]

5. Additional Analyses

We argue that retail depositors may not directly monitor bank financial performance by going through bank financial statements per se, but financially literate customers could be more likely to search for media coverage of banks. Specifically, we measure citizens' search for media coverage of bank-related information (*GOOGLE*) using Google Trends, which count bank-related keywords for each state-year. Bank-related keywords include 'bank,' 'Federal Reserve,' and 'economic' or 'economy.'¹² In the first stage, we regress the Google search for media coverage of bank information (*GOOGLE*) on financial literacy (*FINLIT*) at the state-year level. If financially literate customers are more likely to read bank news, we would expect a significantly positive relationship between *GOOGLE* and *FINLIT*. In the second stage, we interact *FINLIT* with *GOOGLE* and include both variables and their interaction term in the regression model of *ABSDLLP*. If greater attention to media coverage of bank information does not enhance

¹² The search-based index is obtained from Google Trends (https://trends.google.com/trends/) for a given state in a particular month from January 2009 to December 2018. The index is adjusted by the national average and divided by 100, resulting in the scale from -1 to 1. The greater the number on the scale is, the more intensive the search for the queried terms is. We then aggregate the monthly search index to annual level and calculate the mean value for each state-year.

financially literate depositors' monitoring capacity, we would expect the interaction term *FINLIT* **GOOGLE* to be insignificant with *ABSDLLP*.

 $GOOGLE_{t} = \alpha_{0} + \alpha_{1}FINLIT_{t} + \alpha_{2}SIZE_{t} + \alpha_{3}CAPR_{t} + \alpha_{4}EBP_{t} + \alpha_{5}ASG_{t} + \alpha_{6}ZSCORE_{t} + \alpha_{7}\Delta GDP_{t} + \alpha_{8}\Delta UNEMP_{t} + \alpha_{9}\Delta HPI_{t} + STATE_FIXED_EFFECTS + YEAR_FIXED_EFFECTS + \varepsilon_{it}$ (7)

where *GOOGLE* is the index of Google Trends searches of bank-related keywords (including 'bank,' 'Federal Reserve,' and 'economic' or 'economy') for each state-year divided by 100. All control variables in Model (7) are aggregated at the state-level together with state and year fixed effects.

 $ABSDLLP_{it} = \alpha_{it} + \alpha_1 FINLIT_t + \alpha_2 GOOGLE_t + \alpha_3 FINLIT_t * GOOGLE_t + \alpha_4 V_{it} + \alpha_5 W_t + BANK_FIXED_EFFECTS + YEAR_FIXED_EFFECTS + \varepsilon_{it}$ (8)

Variables *ABSDLLP*, *FINLIT*, *V*, and *W* are defined in the same way as in Model (2).

We report the results for regression Model (7) in Panel A of Table 9 and the results for Model (8) in Panel B of Table 9. In Panel A, we find that *GOOGLE* is positively and significantly associated with *FINLIT* at the 1% level (*t*-value = 3.25), suggesting that citizens with higher financially literacy tend to search for more bank-related news via Google. In Panel B, we find that both *FINLIT* and *GOOGLE* have a significantly negative relationship with *ABSDLLP*. However, we do not observe any significance with the interaction term *FINLIT_t* * *GOOGLE_t*, implying that greater attention to media coverage of bank information does not directly relate to financially literate depositors' monitoring.

[Table 9 near here]

In our main regression model, we focus on the discretionary component of LLP because non-discretionary LLP is required, and only discretionary LLP is subject to managerial discretion/manipulation. In a recent study, Chen et al. (2018) discuss the measurement error and inference issues that arise with a two-stage model in this type of estimation of discretionary accruals. Thus, in an additional test, we regress *LLP* on *FINLIT* and all the relevant controls in a single model. We estimate the following regressions models:

$$LLP_{it} = \alpha_{it} + \alpha_1 FINLIT_t + \alpha_2 SIZE_{it} + \alpha_3 CAPR_t + \alpha_4 EBT_{it} + \alpha_5 ASG_t + \alpha_6 ZSCORE_t + \alpha_7 \Delta GDP_t + \alpha_8 \Delta UNEMP_t + \alpha_9 \Delta HPI_t + BANK_FIXED_EFFECTS + YEAR_FIXED_EFFECTS + \varepsilon_{it}$$
(9)

The results in Column 1 of Table 10 show that there is a significant and negative correlation between *LLP* and *FINLIT* at the 10% level (t-value = -1.76), suggesting that financial literacy decreases banks' overall provision for loan losses. For the control variables, we find that bank size (*SIZE*) is significantly and positively associated with *LLP*, indicating that larger banks tend to recognize more loan losses. We also find a significantly negative coefficient of *ASG*, implying that high growth banks are associated with lower loan loss provisions. The coefficient of *ZSCORE* is positive and significant at the 1% level, indicating that banks with high insolvency risks tend to recognize more loan loss provisions.

Depositors would be more concerned about income-increasing provisions, as bank managers have the tendency/incentives to overstate earnings. We identify income-increasing DLLP (i.e., DLLP < 0) and income-decreasing DLLP (i.e., DLLP > 0) from these estimation models and use their absolute values as additional measures of earnings opacity. In a robustness test, we use the absolute value of income-increasing DLLP (ABS_II_DLLP) and income-decreasing DLLP (ABS_II_DLLP) and income-decreasing DLLP (ABS_II_DLLP) and income-decreasing DLLP (ABS_ID_DLLP) as two additional measures of bank opacity. The results in Columns 2–5 of Table 10 show that both ABS_II_DLLP and ABS_ID_DLLP are significantly and negatively associated with FINLIT at the 1% level, consistent with the notion that financial literacy reduces the likelihood of earnings management through DLLP.

[Table 10 near here]

6. Robustness Checks

We are interested in examining whether the influence of *FINLIT* is robust to the inclusion of bank characteristics that would reasonably indicate corporate governance or high stakeholder pressure. Thus, we include two governance variables (i.e., board size and proportion of independent directors) in our regressions as a robustness check. Large boards of directors can commit more time and effort to oversee management (Anderson et al., 2004). Independent directors demand more transparent information to perform their monitoring and advising roles (Armstrong et al., 2014). Board size (*BRDSIZE*) is measured by the number of board directors. The independent director ratio (*INDDIR*) is measured by the number of independent directors divided by the total number of directors. We collect the governance variables (i.e., number of board directors, number of independent directors) from the institutional shareholder services (ISS) database. The results reported in Online Appendix 1 show that *FINLIT* is significantly and negatively associated with *ABSDLLP_A* and *ABSDLLP_B* at the 1% level, even after controlling for corporate governance variables (*BRDSIZE* and *INDDIR*).

Kanagaretnam et al. (2010) find that auditor industry specialization constrains earnings management in an international setting. We also include auditor industry specialization (*AUDIT*) to control for the effect of audit quality on bank transparency. Francis and Wang (2020) document that PwC is a common auditor in bank loans—more common than all the other Big 4 audit firms combined. Hence, we define *AUDIT* as a dummy variable that equals one for a bank audited by PwC and zero otherwise. Consistent with prior literature, the untabulated results show that *AUDIT* is significantly and negatively associated with *ABSDLLP_A* and *ABSDLLP_B*, suggesting that auditor industry specialization constrains bank earnings management. We continue to report a significantly negative association between *ABSDLLP* and *FINLIT* even after

controlling for audit quality. Prior research shows that social capital, which reflects cooperative norms in society, acts as an informal monitoring mechanism, reduces opportunistic behavior, and increases bank accounting quality (Jha & Chen, 2015). We control for social capital, and the untabulated results show that *FINLIT* continues to have a significant and negative association with *ABSDLLP*.

One may be concerned that our results are driven by the external regulatory environment. Large banks are subject to greater government regulations and receive more public attention. For instance, the Federal Deposit Insurance Corporation Improvement Act (FDICIA) of 1991 includes strict requirements for annual audit and management's assessment of the effectiveness of internal control for banks with more than \$1 billion (prior to 2005, more than \$500 million) in assets. We argue that, due to greater visibility, FDICIA banks should be subject to greater depositor monitoring. However, it is also possible that regulatory monitoring may substitute for individual depositors' scrutiny. Therefore, the net effect of regulation is an empirical question. The empirical evidence reported in Panels A and B of Online Appendix 2 shows that FDICIA regulation has insignificant impact on the negative association between financial literacy and *ABSDLLP*.

We examine whether our results are affected by mergers and acquisitions (M&A) activities that may lead to bank managers having different incentives for earnings management. As M&A activities often lead to a large spike in asset growth, we delete banks with more than 10% annual asset growth rate to exclude banks that have potentially engaged in M&A activities. The untabulated results show that *FINLIT* is negatively and significantly associated with *ABSDLLP*, suggesting that financial literacy improves earnings quality among banks without major ongoing M&A activities.

The depositor concentration may influence the association between financial literacy of depositors and banks' earnings management. We partition our sample into two subgroups based on the median value of depositor concentration (measured by the Herfindahl index of bank deposits at the state level). The results reported in Panels A and B of Online Appendix 3 show that *FINLIT* is significantly and negatively correlated with *ABSDLLP* for the subgroups of both high depositor-concentration states and low depositor-concentration states. Therefore, our main results do not seem to be driven by depositor concentration level.

7. Conclusion

Since the 2007–2008 global financial crisis, governments, financial sector experts, and academics have emphasized the role of financial literacy in supporting inclusive and sustainable growth as well as the relationship between financial education and broader financial, economic, and social outcomes (OECD, 2018). Although financial literacy attracts global interest, not much empirical evidence exists to support its perceived role beyond the documented individual or household changes in financial behaviors, such as savings, equity investments, and borrowing.

Our research takes an initial step toward understanding the association between consumer behaviors and aggregate financial and economic outcomes. Banks are known to play a central role in economic and financial stability because they provide liquidity and capital for individuals and businesses. In this study, we provide early evidence on the impact of financial literacy on bank accounting practices. Our empirical results show that financial literacy is negatively related to bank earnings management and, thus, increases bank earnings transparency. We find that retail deposits and consumer loans are two important channels through which financial literacy influences bank transparency. More specifically, we find that it is the stable funding and fewer delinquencies of financially literate depositors/customers that account for our results.

We recognize that our research is subject to certain limitations. Our research employs the NFCS financial literacy data that are aggregated at the state level. Future research could consider investigating the financial literacy of depositors and borrowers at the branch or office level and testing their relationship with bank transparency. This paper focuses on only one type of bank behavior: bank financial reporting transparency in relation to financial literacy. Future prospective studies can expand the scope of our study by examining the impact of citizens' financial literacy on bank capitalization, liquidity, and risk-taking activities.

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Appendix A. Five Financial Literacy Questions from NFCS State-by-State Surveys

The National Financial Capability Study (NFCS) is funded by the FINRA Investor Education Foundation and conducted by ARC Research. The overarching research objectives of the NFCS are to benchmark key indicators of financial capability and evaluate how these indicators vary with underlying demographic, behavioral, attitudinal and financial literacy characteristics. The 2009, 2012, 2015 and 2018 NFCS State-by-State Surveys are nationwide online surveys conducted among over 25,000 American adults. State figures are weighted to be representative of each state in terms of age, gender, ethnicity and education.

In measuring respondents' financial knowledge, the surveys include the following five basic financial concepts questions (correct answer indicated in bold):

1) 'Suppose you had \$100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow?'

- A) More than \$102
- B) Exactly \$102
- C) Less than \$102
- D) Don't know
- E) Refuse to answer

2) 'Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, with the money in this account, would you be able to buy...'

A) More than today

B) Exactly the same as today

C) Less than today

D) Don't know

E) Refuse to answer

3) If interest rates rise, what will typically happen to bond prices?

- A) They will rise
- B) They will fall
- C) They will stay the same
- D) There is no relationship between bond prices and the interest rate
- E) Don't know
- F) Prefer not to say

4) A 15-year mortgage typically requires higher monthly payments than a 30-year mortgage, but the total interest paid over the life of the loan will be less.

- A) True
- B) False
- C) Don't know
- D) Prefer not to say

5) Buying a single company's stock usually provides a safer return than a stock mutual fund.

- A) True
- **B)** False
- C) Don't know
- D) Prefer not to say

Appendix B. Variable Definitions		
Dependent Variables		
ABSDLLP_A	The absolute value of discretionary loan loss provision, calculated as the absolute value of the residual from the regression model (1a): $LLP_{it} = \alpha_0 + \alpha_1 LLA_{it-1} + \alpha_2 NPL_{it-1} + \alpha_3 LOAN_{it} + \alpha_4 \Delta LOAN_{it} + \alpha_5 CHO_{it} + \alpha_6 \Delta NPL_{it} + \alpha_7 \Delta GDP_{it} + \alpha_8 \Delta UNEMP_{it} + \alpha_9 \Delta HPI_{it} + YEAR_DUMMIES + \varepsilon_{it}$	
ABSDLLP_B	The absolute value of discretionary loan loss provisions in year t, calculated as the absolute value of the residual from the regression model (1b): $LLP_{it} = \alpha_0 + \alpha_1 \Delta LOAN_{it} + \alpha_2 CHO_{it} + \alpha_3 \Delta NPL_{it} + \alpha_4 \Delta NPL_{it-1} + \alpha_5 \Delta NPL_{it-2} + \alpha_6 SIZE_{it-1} + \alpha_7 \Delta GDP_{it} + \alpha_8 \Delta UNEMP_{it} + \alpha_9 \Delta HPI_{it} + YEAR_DUMMIES + \varepsilon_{it}$	
ABSDLLPS_A	<i>ABSDLLP_A</i> estimated by the first-stage model by state-year to allow the coefficients on the determinants to vary.	
ABSDLLPS_B	<i>ABSDLLP_B</i> estimated by the first-stage model by state-year to allow the coefficients on the determinants to vary.	
Variables of Interest		
FINLIT	Statewide financial literacy index calculated as the average ratio of correct response to the five financial literacy questions (available in Appendix A) from the 2009, 2012, 2015 and 2018 NFCS State-by-State Surveys. We then use multiple imputation to fill in the years 2010 to 2011, 2013 to 2014, and 2016 to 2017.	
FINLITW	The weighted average <i>FINLIT</i> based on state level deposits (aggregated from branch level data from the FDIC's Summary of Deposits).	
Other Variables		
SIZE	Natural logarithm of total assets (at) from Compustat Bank.	
CAPR	Total equity (ceq) divided by total assets (at) from Compustat Bank.	
EBP	Earnings before loan loss provisions (pi + lntal) divided by total assets (at) from Compustat Bank.	
ASG	Change in total assets (at) divided by lagged total assets (at) from Compustat Bank.	
DTA	Retail deposits (RCON3485 + RCONB563 + RCON3486 + RCON3487 + RCONA529 + RCON3469) divided by total assets (RCFD2170 or RCON2170) from Call Reports. Alternatively, retail deposits (dpdc + cttd + dpsc + mmcd) divided by total assets (at) from Compustat Bank.	
DEPOSIT	Decile rank of DTA.	
CONSUM	Consumer loans (RCFD1975) divided by total loans (RCON2122) from Call Reports. Alternatively, consumer loans (lcacrd) divided by total loans (lntal) from Compustat Bank.	
CLOAN	Decile rank of CONSUM.	
$\Delta DEPT$	Change in deposits (dptc) divided by beginning total assets (at) from Compustat Bank.	
REAL	Real estate loans (RCFD1410) divided by total loans (RCON2122) from Call Reports. Alternatively, real estate loans (lcam) divided by total loans (lntal) from Compustat Bank.	
COMMERC	Commercial and industrial loans (RCFD1763 + RCFD1764 or RCON1766) divided by total loans (RCON2122) from Call Reports. Alternatively, commercial and industrial loans (lcacld) divided by total loans (lntal) from Compustat Bank.	
ROE	Net income (ni) divided by total equity (ceq) from Compustat Bank.	
ZSCORE	Natural logarithm of $(EBP + CAPR)/\sigma(EBP)$ multiplied by -1, where EBP is the mean of earnings before loan loss provisions (pi + lntal) divided by total assets (at) over the sample period; $CAPR$ is the mean of total equity (ceq) divided by total assets (at) over the sample period; and $\sigma(EBP)$ is the standard deviation of EBP over the sample period.	
LLP	Loan loss provision (pll) divided by lagged total loans (lntal) from Compustat Bank.	
	2 Zour 1000 provision (pir) drvided by tagged total loans (intar) from Compustat Dalik.	

BRDSIZE The number of board members (director id) from ISS. INDDIR The number of independent directors (classification == 'I') divided by the total number of directors (director id) from ISS. AUDIT Auditor industry specialization, defined as a dummy variable that equals one for banks audited by PwC, and zero otherwise from Audit Analytics. LLA Loan loss allowance (rcl) divided by total loans (Intal) from Compustat Bank. NPL Nonperforming loans (npat) divided by lagged total loans (Intal) from Compustat Bank. ΔNPL Change in nonperforming loans (npat) divided by lagged total loans (Intal) from Compustat Bank. LOAN Total loans (Intal) divided by total assets (at) from Compustat Bank. ΔLOAN Change in total loans (Intal) divided by lagged total loans (Intal) from Compustat Bank. ΔLOAN Total loans (Intal) divided by lagged total loans (Intal) from Compustat Bank. ΔLOAN Change in total loans (Intal) divided by lagged total loans (Intal) from Compustat Bank. COLLEGE We first create a dummy variable that equals 1 if the survey respondent is a college graduate or with post-graduate education, and 0 otherwise. Then we use COLLEGE to represent the average proportion of NFCS survey respondents who are college graduates for each state-year. INCOME Natural logarithm of per capita income of each state from U.S. Bureau of Economic Analysis. SOCCAP Social capital o		
INDDIR The number of independent directors (classification == 'I') divided by the total number of directors (director id) from ISS. AUDIT Auditor industry specialization, defined as a dummy variable that equals one for banks audited by PwC, and zero otherwise from Audit Analytics. LLA Loan loss allowance (rcl) divided by total loans (Intal) from Compustat Bank. NPL Nonperforming loans (npat) divided by lagged total loans (Intal) from Compustat Bank. ΔNPL Change in nonperforming loans (npat) divided by lagged total loans (Intal) from Compustat Bank. LOAN Total loans (Intal) divided by total assets (at) from Compustat Bank. ΔLOAN Change in total loans (Intal) divided by lagged total loans (Intal) from Compustat Bank. COLLEGE The index of Google Trends searches of bank-related keywords for each state-year divided by 100. Bank-related keywords include 'bank', 'Federal Reserve', and 'Economic' or 'Economy'. We first create a dummy variable that equals 1 if the survey respondent is a college graduate or with post-graduate education, and 0 otherwise. Then we use COLLEGE to represent the average proportion of NFCS survey respondents who are college graduates for each state-year. INCOME Natural logarithm of per capita income of each state from U.S. Bureau of Economic Analysis. SOCCAP Social capital of each state, aggregated from county-level social capital index for the years 1997, 2005, 2009, and 2014, available at Northeast Regional Center for Rural Development (NERCRD). We	СНО	Loan charge-offs (-1*nco) divided by lagged total loans (lntal) from Compustat Bank.
INDDIR of directors (director id) from ISS. AUDIT Auditor industry specialization, defined as a dummy variable that equals one for banks audited by PwC, and zero otherwise from Audit Analytics. LLA Loan loss allowance (rcl) divided by total loans (Intal) from Compustat Bank. NPL Nonperforming loans (npat) divided by lagged total loans (Intal) from Compustat Bank. ΔNPL Change in nonperforming loans (npat) divided by lagged total loans (Intal) from Compustat Bank. LOAN Total loans (Intal) divided by total assets (at) from Compustat Bank. ΔLOAN Change in total loans (Intal) divided by lagged total loans (Intal) from Compustat Bank. ΔLOAN Total loans (Intal) divided by total assets (at) from Compustat Bank. ΔLOAN Change in total loans (Intal) divided by lagged total loans (Intal) from Compustat Bank. GOOGLE divided by 100. Bank-related keywords include 'bank', 'Federal Reserve', and 'Economic' or 'Economy'. We first create a dummy variable that equals 1 if the survey respondent is a college graduate or with post-graduate education, and 0 otherwise. Then we use COLLEGE to represent the average proportion of NFCS survey respondents who are college graduates for each state-year. INCOME Natural logarithm of per capita income of each state from U.S. Bureau of Economic Analysis. SOCCAP Social capital of each state, aggregated from county-level social capital index for the y	BRDSIZE	
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ΔNPL Compustat Bank. LOAN Total loans (Intal) divided by total assets (at) from Compustat Bank. ΔLOAN Change in total loans (Intal) divided by lagged total loans (Intal) from Compustat Bank. GOOGLE The index of Google Trends searches of bank-related keywords for each state-year divided by 100. Bank-related keywords include 'bank', 'Federal Reserve', and 'Economic' or 'Economy'. We first create a dummy variable that equals 1 if the survey respondent is a college graduate or with post-graduate education, and 0 otherwise. Then we use COLLEGE to represent the average proportion of NFCS survey respondents who are college graduates for each state-year. INCOME Natural logarithm of per capita income of each state from U.S. Bureau of Economic Analysis. SOCCAP Social capital of each state, aggregated from county-level social capital index for the years 1997, 2005, 2009, and 2014, available at Northeast Regional Center for Rural Development (NERCRD). We then linearly interpolate the data to fill in the years with missing data. ΔGDP Change in per capita GDP of each state from U.S. Bureau of Economic Analysis.	NPL	Nonperforming loans (npat) divided by lagged total loans (lntal) from Compustat Bank.
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COLLEGE graduate or with post-graduate education, and 0 otherwise. Then we use COLLEGE to represent the average proportion of NFCS survey respondents who are college graduates for each state-year. INCOME Natural logarithm of per capita income of each state from U.S. Bureau of Economic Analysis. SOCCAP Social capital of each state, aggregated from county-level social capital index for the years 1997, 2005, 2009, and 2014, available at Northeast Regional Center for Rural Development (NERCRD). We then linearly interpolate the data to fill in the years with missing data. ΔGDP Change in per capita GDP of each state from U.S. Bureau of Economic Analysis.	GOOGLE	The index of Google Trends searches of bank-related keywords for each state-year divided by 100. Bank-related keywords include 'bank', 'Federal Reserve', and
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SOCCAPyears 1997, 2005, 2009, and 2014, available at Northeast Regional Center for Rural Development (NERCRD). We then linearly interpolate the data to fill in the years with missing data.ΔGDPChange in per capita GDP of each state from U.S. Bureau of Economic Analysis.	INCOME	
	SOCCAP	Development (NERCRD). We then linearly interpolate the data to fill in the years with
AUNEMP Change in unemployment note of each state from U.S. Dungou of Labor Statistics	$\Delta G\overline{DP}$	Change in per capita GDP of each state from U.S. Bureau of Economic Analysis.
Contemposition of the	$\Delta UNEMP$	Change in unemployment rate of each state from U.S. Bureau of Labor Statistics.
Δ <i>HPI</i> Change in house price index of each state from Federal Housing Finance Agency.	ΔHPI	Change in house price index of each state from Federal Housing Finance Agency.
Table 1. Descriptive Statistics

	N	Mean	Q1	Median	Q3	Std. Dev.
ABSDLLP_A _{it}	4,788	0.002	0.001	0.001	0.002	0.002
ABSDLLP_B _{it}	4,788	0.002	0.001	0.001	0.002	0.000
FINLIT _t	4,788	0.596	0.579	0.592	0.609	0.027
SIZE _{it}	4,788	7.578	6.500	7.241	8.392	1.547
CAPR _{it}	4,788	0.104	0.086	0.100	0.120	0.032
EBP _{it}	4,788	0.012	0.009	0.013	0.016	0.007
ASG _{it}	4,788	0.076	0.004	0.046	0.107	0.137
ZSCORE _{it}	4,788	-3.522	-4.055	-3.633	-3.104	0.814
ΔGDP_t	4,788	0.008	0.001	0.013	0.020	0.022
$\Delta UNEMP_t$	4,788	-0.001	-0.010	-0.005	0.001	0.014
ΔHPI_t	4,788	0.008	-0.026	0.016	0.039	0.049

Table 1 provides the descriptive statistics. Bank-level continuous variables are winsorized at top and bottom 1%. All variables are defined in Appendix B.

		1	2	3	4	5	6	7	8	9	10
1	ABSDLLP_A _{it}	1									
2	ABSDLLP_B _{it}	0.924***	1								
3	FINLIT _t	-0.098***	-0.112***	1							
4	SIZE _{it}	-0.085***	-0.072***	-0.028*	1						
5	CAPR _{it}	-0.120***	-0.134***	0.017	0.065***	1					
6	EBP _{it}	-0.161***	-0.185***	0.018	0.296***	0.187***	1				
7	ASG _{it}	-0.087***	-0.098***	0.059***	0.115***	0.102***	0.097***	1			
8	ZSCORE _{it}	0.276***	0.303***	-0.031**	0.006	-0.425***	-0.319***	-0.101***	1		
9	ΔGDP_t	-0.183***	-0.181***	0.002	0.058***	0.118***	0.155***	0.051***	-0.111***	1	
10	$\Delta UNEMP_t$	0.247***	0.232***	-0.009	-0.039***	-0.164***	-0.114***	-0.063***	0.107***	-0.650***	1
11	ΔHPI_t	-0.348***	-0.351***	0.191***	0.115***	0.205***	0.129***	0.207***	-0.143***	0.430***	-0.548***

Table 2. Pearson Correlation Matrix

Table 2 provides the Pearson correlation Matrix. Bank-level continuous variables are winsorized at top and bottom 1%. All variables are defined in Appendix B. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively, based on a two-tailed test.

	Dependent Variable = LLP_{it}	Dependent Variable = LLP_{it}
	(1)	(2)
Variable	Coefficient	Coefficient
variable	(t-Statistic)	(t-Statistic)
Intercent	0.004***	0.003***
Intercept	(6.12)	(4.86)
11 /	-0.160***	
LLA _{it-1}	(-11.50)	
NDI	0.015***	
NPL _{it-1}	(2.89)	
LOAN	0.001**	
LOAN _{it}	(2.23)	
ALOAN	0.003***	0.003***
$\Delta LOAN_{it}$	(5.12)	(4.70)
<u> </u>	1.010***	0.936***
CHO _{it}	(48.40)	(45.97)
	0.096***	0.102***
ΔNPL_{it}	(8.57)	(10.74)
		0.036***
ΔNPL_{it+1}		(4.51)
		0.040***
ΔNPL_{it-1}		(8.64)
		0.017***
ΔNPL_{it-2}		(3.44)
0175		-0.000
<i>SIZE</i> _{it-1}		(-0.61)
	0.007*	0.003
ΔGDP_t	(1.73)	(0.79)
	0.015	0.006
$\Delta UNEMP_t$	(1.39)	(0.49)
	-0.002	-0.003
ΔHPI_t	(-0.75)	(-1.15)
Year Fixed Effects	Yes	Yes
N	5,486	4,825
Adj. R ²	0.874	0.865

Table 3. Estimation of Discretionary Loan Loss Provisions

Table 3 provides the OLS regression results of estimating *DLLP*, with Column 1 displaying Kanagaretnam et al. (2010) model and Column 2 displaying Beatty and Liao (2014) model, respectively. Bank-level continuous variables are winsorized at top and bottom 1%. All variables are defined in Appendix B. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively, based on a two-tailed test. Standard errors are clustered at the state level.

Table 4. Univariate Tests

	Low FINLIT	High FINLIT	Difference	Test of Difference
	Bank-Years	Bank-Years		(t-Statistic)
Mean ABSDLLP_A _{it}	0.0021	0.0018	0.0003	5.21***
Mean ABSDLLP_B _{it}	0.0022	0.0018	0.0004	5.72***
Median ABSDLLP_A _{it}	0.0013	0.0011	0.0002	6.11***
Median ABSDLLP_B _{it}	0.0012	0.0010	0.0002	6.67***

Table 4 compares the differences in the mean values of *ABSDLLP* between banks in low *FINLIT* states and those in high *FINLIT* states. Continuous variables are winsorized at top and bottom 1%. All variables are defined in Appendix B. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively, based on a two-tailed test.

	Dependent Variable	Dependent Variable	Dependent Variable	Dependent Variable
	$= ABSDLLP_A_{it}$	$= ABSDLLP_B_{it}$	$= ABSDLLP_A_{it}$	$= ABSDLLP_B_{it}$
	(1)	(2)	(3)	(4)
Variable	Coefficient	Coefficient	Coefficient	Coefficient
Vallable	(t-Statistic)	(t-Statistic)	(t-Statistic)	(t-Statistic)
Intercent	0.011***	0.012***	0.010***	0.012***
Intercept	(8.37)	(9.23)	(2.80)	(3.11)
	-0.010***	-0.012***	-0.012***	-0.014***
FINLIT _t	(-4.66)	(-5.73)	(-5.72)	(-6.21)
CLZE	-0.00002	-0.00001	0.0003	0.0003
SIZE _{it}	(-1.74)	(-0.81)	(1.24)	(0.62)
CADD	0.004**	0.004**	0.010	0.010
CAPR _{it}	(2.35)	(2.04)	(1.31)	(1.36)
	-0.017*	-0.026***	0.007	-0.003
EBP _{it}	(-1.68)	(-2.81)	(0.52)	(-0.24)
466	0.0002	0.00002	0.001*	0.001*
ASG _{it}	(0.43)	(0.05)	(1.86)	(1.78)
RECORD	0.001***	0.001***	0.001*	0.001*
<i>ZSCORE_{it}</i>	(6.37)	(7.86)	(1.85)	(1.82)
	0.000	0.001	-0.000	-0.000
ΔGDP_t	(0.19)	(0.28)	(-0.25)	(-0.20)
AUNEMD	-0.008	-0.011*	-0.005	-0.008
$\Delta UNEMP_t$	(-1.41)	(-1.69)	(-0.96)	(-1.48)
	-0.007***	-0.008***	-0.007***	-0.007***
ΔHPI_t	(-5.02)	(-4.38)	(-3.60)	(-3.10)
State Fixed Effects	Yes	Yes	, , ,	, <i>, , , , , , , , , , , , , , , , , , </i>
Bank Fixed Effects			Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Ν	4,788	4,788	4,788	4,788
Adj. R ²	0.222	0.239	0.166	0.168

Table 5. Financial Literacy and Discretionary Loan Loss Provisions

Table 5 provides the regression results for the relationship between *FINLIT* and *ABSDLLP*. Columns 1 and 3 provide the regression results of *ABSDLLP_A*. Columns 2 and 4 provide the regression results of *ABSDLLP_B*. Bank-level continuous variables are winsorized at top and bottom 1%. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively, based on a two-tailed test. Standard errors are clustered at the state level.

Table 6. Instrumental Variable Analysis of Financial Literacy and Discretionary Loan Loss Provisions

	Dependent Variable = $FINLIT_t$
	(1)
Variable	Coefficient
variable	(t-Statistic)
Intercept	0.477***
moreept	(12.59)
COLLEGE _t	0.492***
connect the second seco	(3.20)
SIZE _t	-0.001
5122((-0.49)
CAPR _t	-0.062
	(-0.88)
EBP_t	-0.070
	(-0.25)
ASG _t	-0.008
	(-1.14)
<i>ZSCORE</i> _t	0.0002
	(0.04)
ΔGDP_t	-0.034
t	(-1.16)
$\Delta UNEMP_t$	0.193**
t	(2.27)
ΔHPI_t	-0.025
	(-1.21)
State Fixed Effects	Yes
Year Fixed Effects	Yes
N	
N	472
Adj. R ²	0.905

Panel A: First-Stage Regression Results for Predicting Respondents' Financial Literacy

	Dependent Variable =	Dependent Variable =
	ABSDLLP_A _{it}	ABSDLLP_B _{it}
	(1)	(2)
Variable	Coefficient	Coefficient
Variable	(t-Statistic)	(t-Statistic)
Intercont	0.011***	0.013***
Intercept	(3.02)	(3.37)
	-0.014***	-0.016***
PRED_FINLIT _t	(-6.57)	(-6.94)
<u> </u>	0.0004	0.0003
SIZE _{it}	(1.55)	(0.91)
	0.010	0.010
CAPR _{it}	(1.30)	(1.36)
EBP _{it}	0.005	-0.006
	(0.33)	(-0.49)
466	0.001*	0.001*
ASG _{it}	(1.85)	(1.76)
	0.001*	0.001*
ZSCORE _t	(1.82)	(1.82)
	-0.001	-0.001
ΔGDP_t	(-0.46)	(-0.44)
	-0.004	-0.007
$\Delta UNEMP_t$	(-0.79)	(-1.34)
	-0.006***	-0.006**
ΔHPI_t	(-2.75)	(-2.33)
Bank Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
N	4,788	4,788
Adj. R ²	0.167	0.170

Panel B: Second-Stage Regression Results for the Relationship between Predicted FINLIT and ABSDLLP

Table 6 provides the regression results of the instrumental variable analysis for the relationship between *FINLIT* and *ABSDLLP*. Panel A provides the first-stage regression results of predicting *FINLIT*. Panel B provides the second-stage regression results of *ABSDLLP* on predicted *FINLIT*. Bank-level continuous variables are winsorized at top and bottom 1%. All variables are defined in Appendix B. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively, based on a two-tailed test. Standard errors are clustered at the state level.

	Dependent Variable =	Dependent Variable =
	ABSDLLP_A _{it}	ABSDLLP_B _{it}
	(1)	(2)
Variable	Coefficient	Coefficient
variable	(t-Statistic)	(t-Statistic)
Intercept	-0.001	0.001
intercept	(-0.17)	(0.17)
FINLIT _{it}	-0.003	-0.004
	(-0.97)	(-0.96)
DEPOSIT _{it}	0.00002	0.0002
	(0.68)	(0.55)
FINLIT _{it} * DEPOSIT _{it}	-0.002***	-0.002**
	(-3.16)	(-2.24)
SIZE _{it}	0.001*	0.0005
	(1.79)	(1.30)
CAPR _{it}	0.004	0.006
CAIR _{it}	(0.44)	(0.64)
EBP _{it}	0.013	0.002
<i>CDF</i> _{it}	(0.80)	(0.13)
ASG _{it}	0.001	0.001
ASG _{it}	(1.53)	(1.42)
ZSCORE _{it}	0.0004	0.0004
23CORE _{it}	(0.58)	(0.47)
ΔGDP_t	0.0004	0.001
	(0.15)	(0.33)
$\Delta UNEMP_t$	-0.005	-0.007
20 M L M F _t	(-0.74)	(-1.14)
ΔHPI_t	-0.007***	-0.007**
	(-3.13)	(-2.68)
Bank Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
N	3,624	3,624
Adj. R ²	0.168	0.167

Table 7. Financial Literacy	. Retail Denosi	ts. and Discretionarv	Loan	Loss Provisions
Table 7. I manetal Elicitacy	, iteran Deposi	is, and Discretionary	Loan .	

Table 7 provides the regression results for the effect of *DEPOSIT* on the relationship between *FINLIT* and *ABSDLLP*. Column 1 provides the regression results of *ABSDLLP_A* and Column 2 provides the regression results of *ABSDLLP_B*. The *FINLIT* variable in the interaction term *FINLIT*DEPOSIT* is mean centered. Bank-level continuous variables are winsorized at top and bottom 1%. All variables are defined in Appendix B. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively, based on a two-tailed test. Standard errors are clustered at the state level.

	Dependent Variable =	Dependent Variable =
	ABSDLLP_A _{it}	ABSDLLP_B _{it}
	(1)	(2)
Variable	Coefficient	Coefficient
variable	(t-Statistic)	(t-Statistic)
Intercent	0.004*	0.007**
ntercept	(1.72)	(2.43)
	-0.006***	-0.008***
FINLIT _t	(-3.29)	(-3.76)
CLOAN	-0.00002	0.00005
CLOAN _{it}	(-0.59)	(1.27)
	-0.002***	-0.002**
FINLIT _t * CLOAN _{it}	(-2.96)	(-2.34)
	0.0003	0.00001
SIZE _{it}	(1.55)	(0.06)
CAPR _{it}	-0.005	-0.002
	(-0.86)	(-0.39)
	-0.005	-0.011
EBP _{it}	(-0.38)	(-0.73)
A.C.C.	0.001	0.001
ASG _{it}	(1.59)	(1.66)
ZCCODE	0.00004	0.00001
ZSCORE _{it}	(0.07)	(0.19)
	-0.003	-0.003
ΔGDP_t	(-1.59)	(-1.47)
	-0.011	-0.014*
$\Delta UNEMP_t$	(-1.58)	(-1.78)
AUDI	-0.014***	-0.014***
ΔHPI_t	(-5.42)	(-4.18)
Bank Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
N	3,467	3,467
Adj. R ²	0.159	0.159

Table 8. Financial Literacy,	Consumer Lo	oans, and Discretionary	Loan Loss Provisions
Table 0. Financial Littliacy,	Consumer Lo	Jans, and Discictional y	Loan Loss 1 rovisions

Table 8 provides the regression results for the mitigating effect of *CLOAN* on the relationship between *FINLIT* and *ABSDLLP*. Column 1 provides the regression results of *ABSDLLP_A* and Column 2 provides the regression results of *ABSDLLP_B*. The *FINLIT* variable in the interaction term *FINLIT*CLOAN* is mean centered. Bank-level continuous variables are winsorized at top and bottom 1%. All variables are defined in Appendix B. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively, based on a two-tailed test. Standard errors are clustered at the state level.

Table 9. Financial Literacy, Google Search of Bank-Related Information, and Discretionary Loan Loss Provisions

	Dependent Variable = $GOOGLE_t$
	(1)
Variable	Coefficient
variable	(t-Statistic)
Intercept	-0.889***
hereept	(-3.91)
FINLIT _t	0.306***
	(3.25)
SIZE _t	0.005
	(0.94)
CAPRt	-0.100
-	(-1.26)
EBP _t	-0.522
t	(-1.07)
ASG _t	-0.025
	(-1.32)
<i>ZSCORE</i> _t	-0.001
t	(-0.12)
ΔGDP_t	-0.289***
t	(-2.85)
$\Delta UNEMP_t$	0.384
- i	(1.36)
ΔHPI_t	-0.199***
	(-3.01)
State Fixed Effects	Yes
Year Fixed Effects	Yes
N	
N	472
Adj. R ²	0.238

Panel A: Financial Literacy and Google Search of Bank-Related Information

Table 9. (Continued)

	Dependent Variable =	Dependent Variable = $ABSDLLP_B_{it}$ (2)	
	ABSDLLP_A _{it}		
	(1)		
Variable	Coefficient	Coefficient	
	(t-Statistic)	(t-Statistic)	
Intercept	0.010***	0.013***	
	(2.92)	(3.27)	
FINLIT _t	-0.010***	-0.013***	
	(-3.59)	(-3.82)	
GOOGLE _t	-0.001**	-0.002**	
	(-2.05)	(-2.66)	
$FINLIT_t * GOOGLE_t$	-0.013	-0.024	
	(-0.49)	(-0.77)	
SIZE _{it}	0.00004	-0.0001	
	(0.17)	(-0.47)	
CAPR _{it}	0.004	0.006	
	(0.81)	(1.09)	
EBP _{it}	-0.002	-0.010	
	(-0.15)	(-0.75)	
ASG _{it}	0.001*	0.001*	
	(1.98)	(1.89)	
ZSCORE _{it}	0.001	0.001	
	(1.59)	(1.58)	
ΔGDP_t	-0.001	-0.001	
	(-0.47)	(-0.44)	
$\Delta UNEMP_t$	-0.011*	-0.015**	
	(-1.80)	(-2.46)	
ΔHPI_t	-0.010***	-0.010***	
	(-4.67)	(-3.95)	
Bank Fixed Effects	Yes	Yes	
Year Fixed Effects	Yes	Yes	
N	4,788	4,788 4,788	
Adj. R ²	0.164	0.166	

Panel B: The Impact of Google Search of Bank-Related Information on the Relationship between Financial Literacy and Discretionary Loan Loss Provisions

Table 9 provides the regression results for *FINLIT*, Google search of bank-related information, and *ABSDLLP*. Panel A provides the regression results for the relationship between Google search of bank-related information and *FINLIT*. Panel B provides the regression results for the mediating effect of *GOOGLE* on the relationship between *FINLIT* and *ABSDLLP*. Bank-level continuous variables are winsorized at top and bottom 1%. *, **, **** denote significance at the 10%, 5%, and 1% levels, respectively, based on a two-tailed test. Standard errors are clustered at the state level.

	Dependent	Dependent	Dependent	Dependent	Dependent
	Variable =	Variable =	Variable =	Variable =	Variable =
	<i>LLP_{it}</i>	ABS_II_DLLP_A _{it}	ABS_II_DLLP_B _{it}	ABS_ID_DLLP_A _{it}	ABS_ID_DLLP_B _{it}
	(1)	(2)	(3)	(4)	(5)
Variable	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
	(t-Statistic)	(t-Statistic)	(t-Statistic)	(t-Statistic)	(t-Statistic)
Intercept	0.009	0.014***	0.013***	0.011*	0.015**
	(1.01)	(3.44)	(3.12)	(1.79)	(2.48)
FINLIT _t	-0.013*	-0.013***	-0.014***	-0.013***	-0.015***
	(-1.76)	(-4.20)	(-4.12)	(-3.75)	(-4.29)
SIZE _{it}	0.004***	-0.0002	-0.0002	0.0005	0.0001
	(4.76)	(-0.47)	(-0.52)	(1.14)	(0.28)
CAPR _{it}	0.020	0.020**	0.018**	0.005	0.010
	(1.24)	(2.67)	(2.62)	(0.37)	(0.71)
EBP _{it}	0.072	-0.008	-0.011	-0.022	-0.021
	(1.50)	(-0.44)	(-0.60)	(-0.71)	(-0.61)
ASG _{it}	-0.004***	0.002***	0.001***	-0.001	-0.001
	(-3.48)	(3.17)	(2.73)	(-1.27)	(-0.98)
ZSCORE _{it}	0.009***	0.001*	0.001	0.001	0.002
	(4.98)	(1.84)	(1.54)	(0.79)	(1.06)
ΔGDP_t	-0.039***	0.003	-0.001	-0.002	0.001
	(-4.47)	(0.79)	(-0.24)	(-0.79)	(0.21)
$\Delta UNEMP_t$	0.011	-0.000	-0.007	-0.007	-0.010
	(0.56)	(-0.00)	(-0.82)	(-0.72)	(-1.05)
ΔHPI_t	-0.065***	-0.007**	-0.008**	-0.007***	-0.006***
	(-7.95)	(-2.64)	(-2.46)	(-3.40)	(-3.01)
Bank Fixed	Yes	Yes	Yes	Yes	Yes
Effects					
Year Fixed	Yes	Yes	Yes	Yes	Yes
Effects					
N	5,715	2,135	2,135	1,936	1,936
Adj. <i>R</i> ²	0.460	0.201	0.191	0.157	0.184

Table 10. Financial Literacy, Loan Loss Provisions, and Income-Increasing/Decreasing Discretionary Loan Loss Provisions

Table 10 provides the regression results for the relationship between *FINLIT* and loan loss provisions as well as the absolute value of income-increasing discretionary loan loss provisions (*ABS_II_DLLP*) and income-decreasing discretionary loan loss provisions (*ABS_ID_DLLP*). Column 1 provides the regression results of *LLP*. Column 2 provides the regression results of *ABS_II_DLLP_A*. Column 3 provides the regression results of *ABS_II_DLLP_B*. Column 4 provides the regression results of *ABS_ID_DLLP_A*. Column 5 provides the regression results of *ABS_ID_DLLP_B*. Bank-level continuous variables are winsorized at top and bottom 1%. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively, based on a two-tailed test. Standard errors are clustered at the state level.

Online Supplemental Research Materials

Online Appendix 1: The Relationship between Financial Literacy and Discretionary Loan Loss Provisions with Additional Corporate Governance Controls

Online Appendix 2: The Relationship between Financial Literacy and Discretionary Loan Loss Provisions for FDICIA Banks versus Non-FDICIA Banks

Online Appendix 3: The Relationship between Financial Literacy and Discretionary Loan Loss Provisions for Banks in High Depositor Concentration States versus Low Depositor Concentration States