ASIAN ACADEMY *of*
MANAGEMENT JOURNAL
of ACCOUNTING
and FINANCE

AAMJAF Vol. 15, No. 2, 119–154, 2019

DISCRETIONARY LOAN LOSS PROVISION BEHAVIOUR AND BANKS' LIQUIDITY CREATION

Sanzid A. Haq[1], Dung Viet Tran[2]* and M. Kabir Hassan[1]

[1]Department of Economics and Finance, University of New Orleans, 2000 Lakeshore Drive, New Orleans, Los Angeles, 70148 United States
[2]Saigon International School of Business, Banking University Ho Chi Minh City, Ho Chi Minh City 70000, Vietnam

*Corresponding author: dungtv@buh.edu.vn

ABSTRACT

Over the last 30 years, liquidity creation has become a USD12.3 trillion business and large banks seem to have all but secured their indelible footprint in the banking industry. Moreover, over a 24 years period (1984 through 2008) big banks have managed to turn their 76% dominance to a prodigious 86% footprint, while the medium and small banks lost ground in the wake. So, looking for ways to create liquidity has become an existential crisis for non-large banks also an avenue for larger banks to maintain their leads. In an effort to find an innovative way to create liquidity, banks have turned to tools that lend themselves to be manipulated at discretion without material consequence to the rest of the business. Discretionary loan loss provision (DLLP) has become such a tool. Using a large sample of the U.S. bank holding companies from the first quarter of 2000 through the fourth quarter of 2015, we explore the relationship between discretionary loan loss provision and liquidity creation and find that, perhaps much to the dismay of some banks, earning manipulation through a tool like DLLP has a negative impact on liquidity creation. Moreover, this impact is indiscriminate regardless of whether the banks are facing an economy that is marred by financial crisis or otherwise. Our findings stand the test of various sensitivity tests to demonstrate their robustness and consistent with prior findings in the literature.

Keywords: bank liquidity, bank holding company, discretionary loan loss provision, opacity, liquidity creation

Publication date: 31 December 2019

To cite this article: Haq, S. A., Tran, D. V., & Hassan, M. K. (2019). Discretionary loan loss provision behaviour and banks' liquidity creation. *Asian Academy of Management Journal of Accounting and Finance, 15*(2), 119–154. https://doi.org/10.21315/aamjaf2019.15.2.6

To link to this article: https://doi.org/10.21315/aamjaf2019.15.2.6

INTRODUCTION

The opening remark of Deloitte's assessment, "For banks globally, 2018 could be a pivotal year in accelerating the transformation into more strategically focused, technologically modern, and operationally agile institutions, so that they may remain dominant in a rapidly evolving ecosystem", defines what's to come for the banking industry. Although the U.S. banks make up approximately 14% of the global banking industry in terms of assets, the applicability of above premonition is not limited to the global arena alone. The U.S. banking industry can stand to benefit from it as well. Burdened with the complexities of regulations, digital transformation, blurring lines between banks and non-banks and fickle customer base, for many banks getting ready to face what's to come could be all but a daunting challenge. According to a government sponsored site to attract foreign investment into the U.S., last year, in terms of assets, the U.S. banking system cast a USD17.4 trillion shadow over the economy, and it is poised to grow at a staggering 7% this year (SelectUSA.gov, 2017). An impressive outlook of a feat for the industry considering the fact, gross domestic product (GDP) is expected to grow for the country as a whole at a meager 2.9% for the year. According to the data from C. H. Bouwman's site, banks' liquidity has grown from USD2.4 trillion back in 2003 to a colossal USD12.3 trillion in 2015, which is more than a fivefold increase over a little more than a decade. What seems to be fueling this accelerated growth in liquidity is the faster than average growth of creative potential liabilities (loan commitments that are yet to be used) that do not show up in the balance sheet but as a footnote (Berger & Bouwman, 2017).

Liquidity creation is one of the primary reasons why banks exist. Banks as liquidity providers play an important role for the macroeconomy and the financial system. Banks provide necessary liquidity to informationally opaque borrowers without capital market opportunities (Levine & Zervos, 1998), as well as supply liquid funds and payment services to household, which is the main driver for a functioning economy (Kashyap, Rajan & Stein, 2002). In other words, banks simultaneously satisfy the demand for liquidity by the savers and the demand for longer-term financing commitments by the borrowers. Banks also provide loan commitments and other off-balance sheet guarantees that allow customers to plan their investments and expenditures, knowing that the required funds are forthcoming when needed (Holmstrom & Tirole, 1998; Kashyap et al., 2002).

Studies have also shown, (i.e., Fidrmue, Fungáčová, & Will, 2015), that liquidity creation contributes to economic growth and banks' utility value is inextricably related to their ability to transform risks and create liquidity. In their seminal paper Bhattacharya and Thakor (1993) penned, the utility value addition of banks to an economy is through their qualitative asset transformation ability. Although that is not the only niche that banks curved out for themselves but according to Bryant (1980) and again by Diamond and Dybvig (1983), banks' innovative approach to transform short term liabilities, which are customer deposits, into long-term assets, which are invested in the form of long-term loans, bring liquidity relief to depositors and borrowers alike. To add to this measure, Holmstrom and Tirole (1998) and Klapper, Laeven and Rajan (2006), propose that banks' sheer commitments to finance rather than the actual act of financing even have a positive impact on liquidity. Also, in their efforts to create liquidity, banks manage to transform the risk that accompany illiquid loans and the assurances that come with all their liquid deposits (Diamond, 1984; Ramakrishnan & Thakor, 1984; Boyd & Prescott, 1986). Needless to say, it is evident that the degree to which one bank could get an edge over another is contingent on how dexterous each bank is in its qualitative asset transformation ability. To that extent, plethora of studies have delved into finding banks' source to create liquidity. One thing that has emerged from those studies is that, in their efforts to create liquidity, banks have reached into untapped resources like credit risk management tools and manipulate loan loss provision (LLP) to harvest liquidity. Moreover, what makes a tool like LLP a tool of choice for bank managers is the latitude that comes with its discretionary feature. LLP's discretionary feature can be leveraged to meet other resourceful objectives beside strictly precautionary credit risk allowance (Wahlen, 1994). So, we thought we begin with a brief overview of the anatomy of the loan loss provision.

THEORETICAL FRAMEWORK AND HYPOTHESIS DEVELOPMENT

In their role as lenders, banks have learned to live with the risk of default on the loans they extend to their borrowers. As an exposure coping mechanism, banks earmark a proportionate sum as a cushion to dampen any disproportionate loss from loan defaults in any given period, aptly labelled the LLP. Since the practice is in accordance with the Generally Accepted Accounting Principles (GAAP), rather than waiting for actual defaults to happen, banks have the prerogative to realise any expected/projected losses from default periodically through accruals. One of the benefits of the accrual process is that it helps the entities to smoothen the proverbial blow over time at the same time enjoy tax saving through deductions. These deductions may even culminate in higher earning without actually experiencing an outflow from a loss. Although, the hackneyed reference of the motivations behind the accrual practice, which is beyond the scope of our paper, it is worth noting that since segment of the allowance pivot around the discretion of the management, the tool, regardless of its intended use, does lend itself for manipulation by the management to a certain extent. The assertion is echoed by Beatty and Liao (2014) which states, “Although the loan loss provision can be very small compared to net interest income and net non-interest income when economic conditions are good (e.g., 2006–2007), the relative magnitude of this item can balloon during poor economic conditions such as those observed during the recent financial crisis (e.g., 2008–2009). Despite its small magnitude compared to other income statement components, LLP is the largest component among accruals. In addition, the volatility of the provision combined with the discretion in estimating this accrual and the high correlation between the provision and net income make the provision a very important component of the income statement. Specifically, banks’ net income has the highest correlation with LLP at negative 61%, compared to correlations with net interest income, non-interest income and securities gains and losses at 16%, 21% and 15%, respectively.” Our interest lies in exploring the relationship between the discretionary portion of this mercurial resource called the loan loss provision and its impact on liquidity creation.

As mentioned above, the versatility and intent to use discretionary feature of the LLP by banks have been explored by many researchers. There are studies that looked at the behavioural pattern of usage of the provision during the crisis eras and normal business cycle (Laeven & Majnoni, 2003; El Sood, 2012; Agénor & Zilberman, 2015); relationship between pro-cyclical use of the LLP and uncertainty of the financial system as well as the systemic risk (Borio, Furfine, & Lowe, 2001; Wong, Fong, & Choi 2011); accommodating use of LLP and pro-cyclicality (Saurina, 2009; Perez, Salas-Fumas, & Saurina, 2008); the role that LLP plays in managing earnings, regulatory capital, signaling and tax (Lobo & Yang, 2001; Kanagaretnam, Lobo, & Yang, 2005; Anandarajan, Hasan, & McCarthy, 2007; Perez, Salas-Fumas, & Saurina, 2008; Peterson, 2015; 2017a; 2017b; Andries, Gallemore, & Jacob, 2017; Tran, Hassan, & Houston, 2018); LLP allowance discretion by bank managers under various accounting and regulatory country setups (Leventis, Dimitropoulos, & Anandarajan, 2011; Kilic, Lobo, Ranasinghe, & Sivaramakrishnan, 2012; Alali & Jaggi, 2011; Wezel, Chan Lau, & Columba, 2012; Ryan & Keeley, 2013; Hamadi, 2016; Marton & Runesson, 2017); LLP and bank operations (Tran & Ashraf, 2018; Tran, Hassan, & Houston, 2019); LLP and credit competition (Dou, Ryan, & Zou, 2016); relationship between LLP and characteristics of auditor (Kanagaretnam, Lim, & Lobo, 2010; Dahl, 2013); relationship between corporate governance, institutional control and discretionary LLP (Fonseca & Gonzàlez, 2008; Bouvatier, Lepetit, & Strobel, 2014; Curcio & Hasan, 2015); LLP usages, behaviours and practices across countries (Pain, 2003; Bryce, Dadoukis, Hall, & Simper, 2015; Peterson, 2017a; 2017b).

In terms of models used to analyse LLP, Beatty and Liao (2014) analysed nine prevalent models that have been used in the literature to assess LLP. The duo has found that these models differentiate themselves from each other based on the specification they use. Except for one (Collins, Shackelford, & Wahlen, 1995), all of the models use cross-sectional as well as time-series models and each one of them has its own assumptions and stipulations as to which each model considers endogenous or exogenous variables. However, one thing that has been found to be consistent across all the models is, their use of the "Realised Securities Gains and Losses" (RSGL) component in assessing LLP. To carry our analysis, we apply the preferred model identified by Beatty and Liao (2014) for its distinctive ability to isolate discretionary portion from the non-discretionary portion of the provision.

As far as discretionary loan loss provision (DLLP) is concerned, Bouchekoua, Matoussi and Trabelsi (2010), find a relationship between governing board's independence and DLLP valuation. The paper finds that before the era of the landmark legislation of Sarbanes-Oxley Act (SOX), market valued the DLLP of banks higher when it was associated with an independent board versus during the post SOX era. Tran et al. (2018) found that over a 28-year period (1986 through 2013), public banks tended to be more involved in earning management through DLLP than private banks in communicating private information to the investors. They also find evidence of how capital requirements of banks influences DLLP, in accordance with capital management hypothesis. They further conclude that banks with relatively high level of earnings are more likely to manage their earnings via managing DLLP. On the other hand, lower earning banks undertake the opposite strategy. In exploring the information conveyance property of DLLP further, Tran and Ashraf (2018) found that although dividend paying banks tend to manipulate their earning through DLLP less than banks that do not pay dividend, there is a positive relationship between dividend paying banks' choice to use DLLP as a tool to manage earning and the amount of dividend banks pay. As mentioned before, our primary interest lies this discretionary portion of the allowance since it lends itself for manipulation and thought to harnesses power to create, among other things, liquidity. Accordingly, we set out to explore two alternative hypotheses:

H_0: Opacity – Liquidity Contraction hypothesis: Earning management through the practice of DLLP creates less liquidity for banks.

H_A: Opacity – Liquidity Creation hypothesis: Earning management through the practice of DLLP creates more liquidity for banks.

The remainder of the paper flows as follows: the next section illustrates the methodology used to carry out the study and the control measures used to isolate noise from actual impacts. The Data section describes the data and its nuances, and the findings section reports the results. The section subsequent to it discusses robustness of the results as well as possible implications and the last section (Conclusion) summarises the findings of our study.

METHODOLOGY

In exploring the relationship between liquidity creation and earning management through discretionary loan loss provision, we first concentrate on the primary component of our interest, which is the LLP and then isolate the discretionary portion of the provision to better assess its impact on liquidity. We look at quarterly data that span over different business cycle and recent enough to be relevant (2000 through 2015). To minimise distortions from measurement error, we limit our observations in the single homogeneous industry, i.e., bank holding companies. As mentioned earlier, since Beatty and Liao (2014) preferred model have the distinction of isolating discretionary portion of the loan loss provision from the non-discretionary portion better, we use that to capture the pertinent earning management related manipulation. Accordingly, we use the absolute value of the residual of the llp_{it} regression below as proxies for the discretionary portion of the LLP.

$$\begin{aligned} llp_{it} = \alpha + dnpl_{it+1} + dnpl_{it} + dnpl_{it-1} + alw_{it-1} + cho_{it} + size_{it} \\ + dloan_{it} + csret_{it} + dgdp_{it} + dunemp_{it} + \varepsilon_{it} \end{aligned}$$

We then examine the effect of DLLP on liquidity creations by regressing "*catfat*" measure of liquidity, which includes on and off-balance sheet activities, normalised by gross total asset on vector of control variables as well as bank and time specific controls. We are cognizant of the fact that given the complexity of the banking business and the environment in which the industry operates, it is credulous to expect to reduce the spectrum of variables that influence a particular component like liquidity creation to a few variables that we have. Therefore, following Bushman and Williams (2012), to diminish any possible effect from omitted invariant characteristics on our results and reduce correlation across error term, we control for bank specific effect. Similarly, to control for differences in liquidity created by banks over time that are not captured by omitted variables as well as to reduce serial correlation, we controlled for time fixed effect. In addition, it is a presupposition for larger banks to not be involved in earning manipulation through DLLP (Dechow & Dichev, 2002) but larger banks are predisposed to stricter regulatory oversight (Beatty & Liao, 2014). Therefore, banks could be predisposed to certain advantages or disadvantages because of their size and their sheer size could be a window to the market power they might wield in the economy. If the failure of a market behemoth expected to cause consequential or collateral impact in the economy, then larger banks may implicitly enjoy certain assurance that may not be available to the smaller banks. So, relationship between liquidity creation, earning management and profitability may be predicated on size of banks. Smaller banks, however, are prone to internal control weakness and have a higher propensity to restate historic earnings (Doyle, Weili, & McVay, 2007) therefore, we also control for size of the institutions. We use natural log of total assets of individual bank as a proxy for size.

Also, following the leads from the literature (i.e., DeYoung & Roland, 2001; Stiroh & Rumble, 2006), we controlled for equity ratio, earnings and asset growth since these variables are likely to have an impact on performance and liquidity creation. For example, risky banks may be more likely to hold less equity, overextend themselves on loans or enjoy expeditious growth rate. Accordingly, we also controlled for bank level risk since the factor facilitates in isolating the role of capital in supporting the liquidity creation function from the risk transformation function of banks. We use three proxies to measure bank level risk. The first bank level risk measurement proxy we use is the non-performing loans (NPL). Wahlen (1994) reports that both the average market returns and expected future cash-flow increase with discretionary allowances only when predicated on unforeseen defaults and unexpected write-offs. Therefore, we wanted to isolate this factor by controlling for it. Non-performing loans for a particular bank is calculated by dividing the non-performing assets during a particular quarter by the sum of the entire amount of loans that are outstanding of the bank at the start of the very quarter. The second bank risk measurement proxy we use, which is ubiquities in the literature, is the z-score. It measures bank's proximity to the default stage. A larger value indicates lower overall bank risk whereas the lower value indicates to the contrary. It is calculated by summing the return on assets and the result form the capital asset ratio divided by the standard deviation of return on total assets. Since the calculated value tend to be highly skewed, we used the log-transformed value, following the literature (Laeven & Levine, 2009). Following the lead from previous literature (Berger, 2010; Laeven & Levine, 2009) the third measure we use to capture bank risk is through the volatility of its earnings. It is assessed from the standard deviation of the respective banks' earnings.

We test the robustness of our findings by running them through variety of sensitivity tests, bank characteristics, alternative measures of variables and alternative economic specification tests. We rid our findings from endogeneity biases, by performing the Heckman two step selection test, instrumental variable estimation, and propensity matching procedures. To address and eliminate selection bias we carry out the Heckman selection model test (Heckman, Ichimura, & Todd, 1997). In carrying out the test, we first, simulate the probability of liquidity creation by applying a logit selection model and subsequently collect the inverse Mills ratio (*Lambda*) from our main regression (Main findings section) and then estimate the logit liquidity model to calculate the *Lambda*. *Lambda* represents the conditional expectation of the error term from the model selection regression. Subsequently, we re-run our main regression with *Lambda* as an added control variable to mitigate potential self-selection bias.

We explore the endogeneity concerns further through applying propensity score matching (PSM) process. We initiate the process by dividing the sample data into discretionary behaviours quartiles and then, using a logit model, we assess the propensity of a bank engaging the most in earnings management with the control variables. We also add in this logit model an instrument variable, the average of earnings management of the industry (DLLP_AVG). Subsequently, we pair each bank that employs earnings management the most with another bank that has the closet propensity score. We use 0.0005 caliper to minimise the less than desirable matching risk. We use one-to-one matching without replacement, which entails each bank to be used only once, as well as one-to-one matching with replacement, where no matching restriction is applied. To take the PSM process further, we also match each bank that employs earning management the most with two and three other bank holding companies that have the closest propensity scores.

Although PSM takes care of selection bias unfortunately, the threat from unobservable factors which might influence decision to manipulate earning remains unaddressed. To address the latest concern, we use instrumental variable estimation to extract the exogenous element of liquidity creation to test our endogeneity concern further. We use the average DLLP (DLLP_AVG) of the industry as the instrument. We also test for endogeneity bias in our results by using alternate measures of earning management.

We apply the following three alternative models from Beatty and Liao (2014) to reestimate the loan loss provision. A description of the variables can be found in Appendix A.

$$llp_{it} = \alpha + dnpl_{it+1} + dnpl_{it} + dnpl_{it-1} + dnpl_{it-2} + size_{it} + dloan_{it} + csret_{it} + dgdp_{it} + dunemp_{it} + \varepsilon_{it}$$

$$llp_{it} = \alpha + dnpl_{it+1} + dnpl_{it} + dnpl_{it-1} + dnpl_{it-2} + size_{it} + dloan_{it} + alw_{it-1} + csret_{it} + dgdp_{it} + dunemp_{it} + \varepsilon_{it}$$

$$llp_{it} = \alpha + dnpl_{it+1} + dnpl_{it} + dnpl_{it-1} + dnpl_{it-2} + size_{it} + dloan_{it} + cho_{it} + csret_{it} + dgdp_{it} + dunemp_{it} + \varepsilon_{it}$$

We use the above models to isolate the discretionary portion from the non-discretionary portion of the allowance and run our primary liquidity creation regression. To take our testing a little further, we take the advice from previous publications (Scholes, Wilson & Wolfson, 1990; Collins et al., 1995; Beatty & Harris, 1999; Beatty, Ke & Petroni, 2002) and look at other accounts like realized gains and losses from marketable securities (RSGL) which may also be the subject of earning manipulation. We follow the model forwarded by Beatty et al. (2002) to isolate the realised portion from the unrealised portion of the gains and losses from marketable securities and take the residual from the regression to be the discretionary portion of the RSGL.

$$rsgl_{it} = size_{it} + ursgl_{it} + \varepsilon_{it}$$

Last but not least, we test weather liquidity creation is impacted by business cycles (i.e., crisis period vs. non-crisis period). Following Acharya and Mora (2015), we identify three crisis periods: one over the period starting from the third quarter of 2007 through the second quarter of 2008 and the second period extends over the third quarter of 2008 through second quarter of 2009. Although, many may see, what we labelled as, the second period of crisis as an extension of the first one, but Acharya and Mora (2015) make a point to separate the two periods because the separation lends the opportunity to tests whether banks behaviour is predicated on the early or the late stage of the total crisis period. By the way, for completeness sake, we assess the impact over both the above-mentioned crisis periods in continuum, which is the third period we consider.

Our contributions to the literature are three-fold. We believe our study is the first of its kind which explores the relationship between discretionary earning management through a tool like DLLP and liquidity creation in a long-term and within a single industry setting. Our concentrated approach make way for our findings to be more precise, accurate and robust. Since our study spans over crisis as well as non-crisis periods, our findings are free of sample selection bias. Our paper also uses quantile regression to study earning management behaviours of banks throughout the quantiles which is a first in the literature with respect to liquidity creation and earning management. Lastly, by focusing on one of the existential features of banks, findings from our study can go a long way in understanding the complex relationship between discretionary opportunity to manage earning and creating liquidity.

DATA

For our analysis, we used quarterly data from Federal Reserve's Report of Condition and Income Call report for all U.S. bank holding companies for the period starting at the first quarter of 2000 through the fourth quarter of 2015. We purged all non-commercial banks related data from our sample. In cleaning the data further, to allow for more coherent analysis, we purged observations with missing or incomplete financial data, "counter-intuitive" data related to income statement related components such as negative interest expenses, negative salary/wages related expenses or other negative non-interest expenses. Furthermore, following Berger, El Ghoul, Guedhami and Roman (2016), we rounded up all shareholder equity ratio of less than 1% (<1%) to 1%, to avoid artificially elevated misspecification in any other resulting ratios, following Berger and Bouwman (2013) dropped observations which had total assets of less than or equal to USD25 million, outstanding loans or deposits balance of zero or less than zero, and winsorised any outlier ratios at the 1% to the lowest and 99% at the highest, to diminish any impacts of extreme outliers. We retain observations with negative equity balance, as Berger and Bouwman (2013) did, for any informative power they may possess as well. The final sample data set contains 34,367 bank-quarter observations generated by 1,817 bank holding companies over the 16-year period.

Table 1
Summary statistics

Variables	Observation	Mean	SD	Minimum	Maximum
LC	34,367	0.457	0.174	(0.027)	0.899
DLLP	34,367	0.004	0.006	0.000	0.074
SIZE	34,367	13.930	1.236	12.089	19.109
CAP	34,367	0.090	0.028	0.019	0.220
EARNINGS	34,367	0.015	0.009	(0.020)	0.051
GROWTH	34,367	0.016	0.042	(0.085)	0.229
NPL	34,367	0.018	0.022	0.000	0.118
Z-SCORE	34,367	43.407	37.828	0.465	197.907
SD(EARNINGS)	34,367	0.005	0.007	0.001	0.047

The average liquidity created by the banks in our sample period is 0.457 which is about in the middle of the spectrum (min. of –0.027 and max. of 0.899), effectively not impacted by extreme outliers. Although, most banks fall in and around the mean, in terms of using DLLP to manage earning, there seems to be some outliers which use the techniques (DLLP) quite often to manage their earnings. Average size banks hold about USD2.6 billion (ln 13.93) of total assets and most of the banks fall within 1.26 standard deviation of the mean. An average bank in the sample has an equity ratio of 9% and earnings of 1.5% of total assets with low earning volatility. Although an average bank is growing about 1.6% and carries about 1.8% of non-performing loans in their asset portfolio, there seems to be some extreme outliers. Last but not the least, the average z-score of the banks is 43.41 which indicates that the average bank in our sample is quite far from a default risk.

Table 2 portrays how the key variables are correlated with each other. Although, all of the correlations among the variables are significant at the 1% level, there are a few relationships that might be worth drawing your attention to. DLLP is negatively correlated with liquidity creation (LC) meaning, banks that tend to manage their earnings less through DLLP are more likely to create more liquidity, confirming our Opacity – Liquidity Contraction hypothesis (H_0), which is, banks that tend to manage their earnings more through DLLP are likely to create less liquidity (LC). Similarly, banks with lower equity ratio tend to create more liquidity and are less likely to be involved in earning management through DLLP. On the other hand, banks that tend to grow over time in terms of earnings, tend to create liquidity but tend not to use DLLP to manipulate their earnings. The table also shows that banks that maintain stable earnings, are less risky or have lower non-performing loans, tend to create liquidity. However, banks with high earning volatility and higher non-performing loans tend to be involved in manipulating earnings through DLLP more and so do risky banks.

Table 2
Correlation statistics

	LC	DLLP	SIZE	CAP	EARNINGS	GROWTH	NPL	Z-SCORE	SD(EAR)
LC	1								
DLLP	–0.0843*	1							
SIZE	0.1388*	0.0258*	1						
CAP	–0.1927*	–0.0321*	0.0506*	1					
EARNINGS	0.1299*	–0.1803*	0.1137*	0.3578*	1				
GROWTH	0.1221*	–0.1110*	0.0414*	–0.0298*	0.1516*	1			
NPL	–0.1152*	0.4265*	0.0643*	–0.1296*	–0.3616*	–0.2246*	1		
Z-SCORE	–0.0201*	–0.2700*	0.0426*	0.2275*	0.2588*	0.1093*	–0.3888*	1	
SD(EAR)	–0.0913*	0.2599*	0.1108*	0.0322*	–0.1782*	–0.1164*	0.3544*	–0.4211*	1

Note: ***, **, * indicate significance at the 1%, 5%, and 10% level respectively

Does Bank Opacity Affect Liquidity Creation?

Main findings

Turning our focus back to exploring the primary hypothesis of our paper, we estimate the empirical specification by regressing liquidity of bank i at time t (LC_{it}) on DLLP of bank i at time $t-1$ $(DLLP_{it-1})$, vector of control variables of bank i at time $t-1$ ($Control\ Variable_{it-1}$), quarter fixed (ϑ_t) effects (γ_i) for time effects, bank fixed effect to control for unobservable bank characteristics and the error term (ε_{it}). In other words:

$$LC_{it} = \alpha+DLLP_{it-1}+Control\ Variable_{it-1}+\gamma_i+\vartheta_t+\varepsilon_{it}$$

Since, over time, banks' discretionary earning management behaviours (DLLP) have the potential to be correlated within a bank, standard errors are clustered by bank so assessed significance are corrected for heteroscedasticity. Since DLLP is likely to be correlated to individual banks over time as well, it might pose an endogeneity problem. So, to mitigate the effect from possible reverse causality, we take an additional measure of lagging bank level variables by a quarter in every regression.

We presented our primary findings in Table 3. Column 1 reports our baseline model. After controlling for previously mentioned control variables, the expected average LC of banks is 0.855 and statistically significant. The coefficient on our main variable of interest, DLLP, is negative and statistically significant at the 1% level, suggesting that banks which engage less in earning management through DLLP create more liquidity. The economic magnitude of this effect is also significant. One standard deviation increase in DLLP, caeteris paribus, results in a decrease of LC of 0.067 (i.e. the coefficient on DLLP, –0.385, times the standard deviation of LC, 0.174). The move translates to a 14.6% decrease in LC (.0067 divided by .457). This finding is consistent with our H_0, showing that LC is decreased in opaque banks. The evidence is also in line with the findings of Díaz and Huang (2017) which finds better-governed banks create higher levels of liquidity. Prior literature suggests that managers have incentives to manage accounts in the 4th quarter than in other quarters (Liu, Ryan & Wahlen, 1997), therefore, we ran the regression using only the 4th quarter data, and the results remain constantly negative and statistically significant coefficient.

Table 3
Baseline multivariate analysis

	Baseline	Only 4th quarter	Exclude crisis time	Lag of 4 quarters instead of 1 quarter	Exclude M&A with 20% assets growth	Alternative econometric			
						Prais	Newey-West	Fama-MacBeth	Cluster two way
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
DLLP	–0.385***	–0.652***	–0.315**	–0.507***	–0.363***	–0.113***	–0.930***	–2.397***	–0.930*
	(0.116)	(0.214)	(0.139)	(0.128)	(0.116)	(0.034)	(0.212)	(0.467)	(0.483)
SIZE	–0.028**	–0.029**	–0.026**	–0.028**	–0.031**	0.023***	0.021***	0.017***	0.021***
	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)	(0.003)	(0.002)	(0.001)	(0.005)
CAP	–0.290**	–0.325***	–0.356***	–0.245*	–0.280**	–0.107***	–1.539***	–1.164***	–1.539***
	(0.118)	(0.126)	(0.128)	(0.127)	(0.120)	(0.035)	(0.062)	(0.160)	(0.175)
EARNINGS	1.485***	1.771***	1.634***	1.139***	1.491***	0.081***	3.252***	3.568***	3.252***
	(0.166)	(0.224)	(0.190)	(0.175)	(0.166)	(0.028)	(0.195)	(0.695)	(0.606)
GROWTH	–0.011	–0.029	–0.002	0.018	–0.012	0.007*	0.265***	0.175**	0.265***
	(0.014)	(0.028)	(0.015)	(0.015)	(0.013)	(0.004)	(0.025)	(0.073)	(0.058)
NPL	–0.770***	–0.671***	–0.743***	–0.809***	–0.774***	–0.285***	–0.626***	–0.709***	–0.626***
	(0.104)	(0.106)	(0.119)	(0.120)	(0.104)	(0.030)	(0.074)	(0.186)	(0.157)
Z-SCORE	0.000	0.000	0.000	0.000	0.000	0.000***	–0.000***	–0.001***	–0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SD(EARNINGS)	–0.130	–0.217	–0.310	–0.038	–0.133	–0.266***	–1.472***	–1.600***	–1.472***
	(0.249)	(0.279)	(0.279)	(0.260)	(0.248)	(0.097)	(0.247)	(0.364)	(0.553)

(*continue on next page*)

Table 3 (*continued*)

	Baseline	Only 4th quarter	Exclude crisis time	Lag of 4 quarters instead of 1 quarter	Exclude M&A with 20% assets growth	Alternative econometric			
						Prais	Newey-West	Fama-MacBeth	Cluster two way
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	0.855***	0.892***	0.832***	0.883***	0.892***	0.138***	0.295***	0.312***	0.295***
	(0.170)	(0.185)	(0.179)	(0.187)	(0.172)	(0.041)	(0.022)	(0.020)	(0.064)
Observations	34,367	8,560	28,091	30,498	34,007	34,367	34,367	34,367	34,367
Adj R^2	0.247	0.239	0.251	0.244	0.251	0.301		0.123	0.117
Bank FE	Yes	Yes	Yes	Yes	Yes				
Time FE	Yes	Yes	Yes	Yes	Yes				
# clusters	1,817	1,748	1,811	1,662	1,816				

Note: Robust standard errors in parentheses, ***, **, * indicate significance at the 1%, 5%, and 10% level respectively.

One may argue that our main results could be driven by crisis periods, which usually bring about large structural breaks in risk profile and liquidity creation (Adhikari & Agrawal, 2016). To address this concern, we repeat our main model by excluding the crisis period (2007:Q3–2009:Q2) in Column 3. This subsample also allows us to investigate whether banks that engage in earnings management create less liquidity during normal times. As the results in column 3 show, the inverse relationship continues to hold between DLLP and LC and it gives credence to the fact that our main results are not merely driven by crises. It is worth noting that the coefficient and *t*-statistics of DLLP decreased slightly, suggesting that the relation between DLLP and LC may not vary during the crisis.

In exploring the relationship further, following Berger et al. (2016), we lagged the variables four quarters instead of one quarter (column 4) and excluded merger and acquisition (M&A) banks with 20% asset growth (column 5) which might indicate the presence of M&A activities since LC is known to have been impacted by merger status of banks (Berger & Bouwman, 2009). The derived coefficient of all the imposed parameters are virtually similar in magnitude and significance to that of our baseline case.

To test whether our results stand the test of different econometric approaches, we carried out the Paris-Winsten test to take care of serial correlation (column 6), Newey-West test to produce consistent estimates in case there is autocorrelation in addition to possible heteroskedasticity (column 7), Fama-MacBeth process to address challenges that come with panel data (column 8) and finally, two-way cluster procedure to correct for both cross-sectional correlation and serial correlation (column 9). Results from the added specifications are similar in magnitude and significance to that of our baseline case.

Although not shown in the table, we have also measured the DLLP's persistency on LC with 8 and 12 quarter lagged variables, pushed the envelope by simulating M&A activity by excluding banks with 40% asset growth, assessed the influence of the three risk proxies [NPL, Z-SCORE and SD(EARNINGS)] individually, as well as included a state dummy to control for environment effects. We are happy to report that results from the additional measures are inline with our primary findings, in terms of significance and virtually similar in magnitude.

LC appears to be related to other bank characteristics as well. We find that smaller, less capitalised banks, banks with low non-performing loan on their books tend not to engage in earning management feature of DLLP to create liquidity. On the other hand, larger, well-capitalised banks with high growth and higher non-performing assets on their books are more likely to engage in earnings management to create liquidity. We also find that highly profitable banks with lower earnings volatility tend to create more liquidity. Although we find low growth and low earnings volatility banks create more liquidity, but the coefficients are not statistically significant. In summary, our findings support the H_0, which is, banks that manipulate their reported numbers, become more opaque and create less liquidity.

Liquidity Creation Across Banks – A Quantile Regression

To purge our fear of any interrelationship between LC and DLLP across different distribution of banks' LC, we carried out quantile regression. The ubiquitously used OLS approach (the ordinary least squares), as we ourselves used in this endeavor, is geared towards capturing the average behaviour of the sample with the assumption of the homogeneity of the effects of the variables. The advantage that quantile regression offers over the traditional OLS approach is that it gives the opportunity to investigate possible conditional heterogeneity (Tran et al., 2018) as well as it relaxes the restrictive assumption of normal distribution of error terms across observations (Klomp & Haan, 2012). The findings are reported in Table 4. Our variable of interest (DLLP) continues to have a negative coefficient and remains statistically significant for the most part, except for 10th, 80th and 90th percentiles. Therefore, we observe a V-shape impact of DLLP on LC as the quantiles increase. The pattern of the impact suggests a marginal effect of DLLP on LC differ across the quantiles of LC.

In summary, the results indicate that DLLP not only affects the conditional average of LC, but also influences the distribution of LC. They also suggest that high liquidity created banks, leveraged by higher degree of DLLP, are less likely to decrease their LC. In other words, the impact on the LC appears to be less profound for highly liquidity creating banks. These results taken together support our previous findings.

Table 4
Liquidity creation with different quantiles

	Quantile (Dependent variable = LC)								
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
DLLP	–0.399	–0.756***	–1.044***	–0.884***	–0.669***	–0.640***	–0.429**	–0.317	–0.090
	(0.448)	(0.180)	(0.289)	(0.213)	(0.204)	(0.195)	(0.214)	(0.203)	(0.301)
SIZE	0.017***	0.025***	0.026***	0.027***	0.027***	0.027***	0.026***	0.024***	0.023***
	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
CAP	–1.806***	–1.721***	–1.646***	–1.607***	–1.545***	–1.487***	–1.413***	–1.388***	–1.259***
	(0.062)	(0.051)	(0.039)	(0.039)	(0.038)	(0.031)	(0.041)	(0.038)	(0.051)
EARNINGS	2.529***	2.623***	2.758***	3.095***	3.213***	3.503***	3.675***	4.269***	4.557***
	(0.270)	(0.240)	(0.167)	(0.158)	(0.151)	(0.146)	(0.170)	(0.173)	(0.189)
GROWTH	0.165***	0.220***	0.237***	0.228***	0.248***	0.282***	0.329***	0.378***	0.415***
	(0.043)	(0.027)	(0.023)	(0.021)	(0.026)	(0.026)	(0.035)	(0.028)	(0.029)
NPL	0.153*	–0.312***	–0.502***	–0.689***	–0.837***	–0.921***	–1.027***	–1.087***	–1.477***
	(0.091)	(0.079)	(0.076)	(0.056)	(0.045)	(0.045)	(0.060)	(0.049)	(0.068)
Z-SCORE	–0.000***	–0.000***	–0.001***	–0.001***	–0.000***	–0.000***	–0.000***	–0.000***	–0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SD (EARNINGS)	–3.332***	–2.561***	–2.286***	–1.844***	–1.508***	–1.197***	–0.755***	–0.041	0.993**
	(0.277)	(0.295)	(0.273)	(0.255)	(0.176)	(0.164)	(0.221)	(0.314)	(0.443)
Constant	0.167***	0.135***	0.167***	0.186***	0.221***	0.247***	0.290***	0.343***	0.425***
	(0.038)	(0.014)	(0.014)	(0.012)	(0.012)	(0.010)	(0.011)	(0.012)	(0.017)
Observations	34,367	34,367	34,367	34,367	34,367	34,367	34,367	34,367	34,367
R^2	0.0951	0.0951	0.0951	0.0951	0.0951	0.0951	0.0951	0.0951	0.0951

Note: Robust standard errors in parentheses, ***, **, * indicate significance at the 1%, 5%, and 10% level respectively.

How Does the Size Effect Affect the Relation between Bank Opacity and Liquidity Creation?

We also gage the scale effect of LC via DLLP manipulation. Kwan (2004) reports that in an effort to compete, complemented by their funding sources, one of the features that makes national and regional banks stand apart from community banks is the product mix each one of them offers to their respective customers. Inherent from their size, larger banks jut out beyond the limitations of their smaller counter parts to cater non-traditional banking needs and leave more traditional lending activities to the smaller banks. However, as Collins et al. (1995) shown, although larger banks may enjoy the apparent size advantage but that very feature may also act as a double-edged sword. Because of their realm of influence and systemic entanglement with the economy at large, they (large banks) become target of greater scrutiny, greater market discipline due to uninsured financiers and disclosure burdens by regulatory agencies. Therefore, it is obvious that bank size has the potential of influencing our findings. Since, for the most part, bank size is driven by banks' own discretion, it is highly probable that size may also be highly correlated with other independent as well as dependent variables.

In column 1 of Table 5, we mitigate the above-mentioned autocorrelation effect by following the process outlined by De Jonghe (2010). The paper uses an innovative process to deduce actual effect of bank size on bank profit by regressing profitability measures on all relevant variables except for the size variable. The objective of the process was to isolate how much of the profitability is due to operation decisions and how much of it is due to size. The operational impact is measured by the fitted value and the size impact, therefore, tantamount to the residual. We adopted the process because it orthogonalises the size with respect to the other variables and allows us to derive the actual impact of size. In column 2, we check the nonlinear relationship between earnings management and size. Following Ellul and Yerramilli (2013), we include the size-decile fixed effects to control for unobserved heterogeneity across different sizes of banks. To mitigate the size outlier, we filter our data to leave out the top ten biggest banks and re-run our primary regression. The results continue to be in line with our primary findings.

Also, to see DLLP and LC relationship across bank size, we run three other models with banks that have assets of less than USD1 billion (column 3), banks that have assets more than USD1 billion but less than USD5 billion (column 4) and those that have assets more than USD5 billion (column 5). We find that, for small banks, DLLP and LC are negatively correlated and significant, while this relationship is insignificant for medium and large banks. Thus, the data suggests that, consistent with our economic intuition, the H_0 dominates for small banks, but not for medium and large banks.

Table 5
Liquidity creation based on bank size

	Size residual	Size decile	Excl Top 10th	Small banks	Medium banks	Large banks
	(1)	(2)	(3)	(4)	(5)	(6)
DLLP	–0.324***	–0.388***	–0.338***	–0.364***	–0.215	–0.567
	(0.115)	(0.114)	(0.116)	(0.124)	(0.216)	(0.508)
SIZE	0.019***		–0.035***	–0.077***	0.011	–0.034
	(0.005)		(0.012)	(0.015)	(0.020)	(0.055)
CAP	–0.367***	–0.275**	–0.482***	–0.897***	0.058	1.302***
	(0.120)	(0.118)	(0.117)	(0.148)	(0.195)	(0.478)
EARNINGS	1.838***	1.475***	1.586***	1.378***	1.505***	1.194***
	(0.219)	(0.166)	(0.178)	(0.210)	(0.275)	(0.318)
GROWTH	0.000	–0.016	–0.013	–0.019	–0.022	0.027
	(0.015)	(0.013)	(0.015)	(0.017)	(0.021)	(0.030)
NPL	–0.737***	–0.785***	–0.829***	–0.942***	–0.610***	–0.518
	(0.106)	(0.104)	(0.102)	(0.108)	(0.186)	(0.403)
Z-SCORE	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SD(EARNINGS)	0.011	–0.135	–0.193	–0.641	0.016	0.182
	(0.253)	(0.246)	(0.267)	(0.454)	(0.325)	(0.568)
Constant	0.465***	0.507***	0.957***	1.515***	0.321	0.929
	(0.012)	(0.016)	(0.155)	(0.205)	(0.277)	(0.901)
Observations	33,759	34,367	30,920	19,584	11,255	3,528
Adj R^2	0.239	0.247	0.258	0.269	0.240	0.273
# clusters	1,817	1,817	1,716	1,413	539	152
BFE	Yes	Yes	Yes	Yes	Yes	Yes
TFE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses, ***, **, * indicate significance at the 1%, 5%, and 10% level respectively.

ROBUSTNESS TESTS

Alternate Measures of Earning Management

Table 6 shows reestimation of our baseline model with alternative measures of bank earnings management as a robustness check of our findings. In column 1, to neutralise the effects from outliers, we run our base model with natural logarithm of DLLP. Inspired by Foos, Norden and Weber (2009), next, we use DLLP deviation of individual bank (*i*) in each quarter (time *t*) from the average DLLP of the industry at time *t* as a measure of banks' earnings management. We find the results to be similar to that of our primary findings.

For the next three models (columns 3 through 5), we apply the three alternative models from Beatty and Liao (2014) to compute DLLP. For our last alternative measure of earning management model, we look at other account, like RSGL from marketable securities, which could also be a subject of earning manipulation (Collins et al., 1995; Beatty & Harris, 1999; Beatty et al., 2002). We follow the model forwarded by Beatty et al. (2002) to isolate the realised portion from the unrealised portion of the gains and losses from marketable securities and take the residual from the regression as proxy for the discretionary portion of the RSGL. The results confirm our main findings which is, banks that engage less in earning management through discretionary loan loss provision (DLLP) create more liquidity. All the coefficients have the same sign as our primary results and same statistical significance. It is worth noting that our variable of interest (DLLP) in the RSGL model has the same sign as our primary results but just not statistically significant.

Table 6
Alternate measure of earning management (EM)

	LN(EM)	Deviation EM	EM1	EM2	EM3	RSGL
	(1)	(2)	(3)	(4)	(5)	(6)
DLLP	–0.002***	–0.385***	–0.243***	–0.452***	–0.382***	–0.670
	(0.000)	(0.116)	(0.075)	(0.087)	(0.115)	(1.588)
SIZE	–0.028**	–0.028**	–0.027**	–0.027**	–0.028**	–0.025**
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
CAP	–0.285**	–0.290**	–0.296**	–0.298**	–0.290**	–0.282**
	(0.118)	(0.118)	(0.118)	(0.118)	(0.118)	(0.118)

(*continue to next page*)

Table 6 (*continued*)

	LN(EM)	Deviation EM	EM1	EM2	EM3	RSGL
	(1)	(2)	(3)	(4)	(5)	(6)
EARNINGS	1.495***	1.485***	1.476***	1.453***	1.486***	1.526***
	(0.166)	(0.166)	(0.167)	(0.167)	(0.166)	(0.165)
GROWTH	–0.010	–0.011	–0.013	–0.014	–0.011	–0.010
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
NPL	–0.775***	–0.770***	–0.770***	–0.749***	–0.771***	–0.787***
	(0.104)	(0.104)	(0.104)	(0.104)	(0.104)	(0.103)
Z-SCORE	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SD(EARNINGS)	–0.124	–0.130	–0.119	–0.116	–0.130	–0.139
	(0.249)	(0.249)	(0.249)	(0.249)	(0.249)	(0.245)
Constant	0.844***	0.854***	0.848***	0.847***	0.855***	0.815***
	(0.170)	(0.170)	(0.170)	(0.170)	(0.170)	(0.170)
Observations	34,367	34,367	34,367	34,367	34,367	34,926
Adj R^2	0.247	0.247	0.247	0.248	0.247	0.242
# clusters	1,817	1,817	1,817	1,817	1,817	1,827
BFE	Yes	Yes	Yes	Yes	Yes	Yes
TFE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses, ***, **, * indicate significance at the 1%, 5%, and 10% level respectively.

Alternative Measures of Liquidity Creation

Table 7 shows reestimation of our baseline model with alternative measures of bank LC to augment our robustness check. In column 1, inspired by Foos et al. (2010), Tran et al. (2018), we use LC deviation of individual bank (*i*) in each quarter (time *t*) from the average LC of the industry at time *t* as a measure of banks' LC. We find the results to be similar to that of our primary findings.

Berger and Bouwman (2009) reports that since the mid-1990s, off-balance sheet sourced liquidity creation has surpassed, and even taken on an accelerated growth mode, compares to on-balance sheet sourced liquidity creation. This transposition is primarily spurred from the growth in idle loan commitments. So, following Berger and Bouwman's (2009) advice, we wanted to explore the relationship between our EM variable of interest (DLLP) and the all-inclusive measure of liquidity which takes into account both on and off-balance sheet activities. We run our main regression with LC_ON, and LC_OFF as the dependent variables, where LC_ON represents the weighted sum of banks' on-balance sheet and LC_OFF represents the off-balance sheet variables. Weights are assigned based on the liquidity of each item. Results of our exploration are similar in magnitude and significance to that of our main findings.

Table 7
Alternative measure of LC

	Deviation LC	LC_ON	LC_OFF
	(1)	(2)	(3)
DLLP	–0.385***	–0.175***	–0.254***
	(0.116)	(0.037)	(0.098)
SIZE	–0.028**	–0.004	–0.024**
	(0.012)	(0.004)	(0.009)
CAP	–0.290**	–0.049	–0.242**
	(0.118)	(0.035)	(0.100)
EARNINGS	1.485***	0.373***	1.111***
	(0.166)	(0.061)	(0.128)
GROWTH	–0.011	0.020***	–0.034***
	(0.014)	(0.005)	(0.011)
NPL	–0.770***	–0.314***	–0.434***
	(0.104)	(0.033)	(0.083)
Z-SCORE	0.000	0.000**	0.000
	(0.000)	(0.000)	(0.000)
SD(EARNINGS)	–0.130	–0.133	0.044
	(0.249)	(0.096)	(0.188)
Constant	0.448***	0.156***	0.697***
	(0.170)	(0.053)	(0.129)
Observations	34,367	34,367	34,367
R^2	0.129	0.389	0.127
# clusters	1,817	1,817	1,817
BFE	Yes	Yes	Yes
TFE	Yes	Yes	Yes

Note: Robust standard errors in parentheses, ***, **, * indicate significance at the 1%, 5%, and 10% level respectively.

Endogeneity Concerns

While we have been focused on finding the relationship between the uncharted effect of DLLP on creating liquidity (LC), our effort would be remiss if we did not address the endogeneity or sample selection bias that could plague our results. Our purpose in this section is to obtain a robust understanding of the role opaqueness of banks plays on liquidity creation. The concept of causation can turn out to be tricky. Take for an instance, the relationship between characteristics like opaqueness and LC. One may ponder whether certain characteristic, like low opaqueness, lead a bank to create less liquidity, or does low level of LC usher in low transparency (i.e. lower-opaque) in an institution?

Therefore, we end our analysis of the topic by shedding light on whether the results of our analysis are products of unobservable variables, biased sampling, or suffers from serial or autocorrelation as well as possible heteroscedasticity. Throughout our analysis, we controlled for bank and quarter fixed effects to diminish any possible effect from omitted invariant characteristics or differences in LC by banks that can arise over time that are not manifested by omitted variables. These measures also minimise serial correlation. As mentioned earlier in the study, to test whether our results stand the test of different econometric approaches, we carried out the Paris-Winsten test, to take care of serial correlation, Newey-West test, to produce consistent estimates in case there is autocorrelation in addition to possible heteroscedasticity, Fama-MacBeth process, to tackle the challenges of panel data and, last but not least, two-way cluster procedure, to correct for both cross-sectional correlation and serial correlation.

We further augment our estimation with the Heckman selection model, the instrumental variables approach and the propensity score matching methods. We carried out these procedures to control for any selection bias that could be present in our estimations. Table 8 captures the results and the testing processes are described below it.

We first start with performing the two-step Heckman test to explore whether our variable of interest, LC, possibly be correlated with the discretionary choice of the loan loss provision (DLLP). Following Chen, Huang, and Zhang (2016), we begin by dividing the full sample into three groups according to the degree of LC. We assign the value of 1 if banks belong to the group that creates the most liquidity (1st tercile), and 0 if banks belong to the group that creates the least liquidity (3rd tercile). We use logit selection model to select LC groups and then obtain the inverse Mills ratio (IMR), which represents the omitted variable in our primary equation. IMR represents the conditional expectation of the error term from the model selection regression, predicated on observable characteristics and decision to create liquidity of banks. Following Laeven and Levine (2007) and Tran (2019), we use the average LC of other banks as an instrument variable. We then estimate the logit LC-choice model and calculate the IMR again. This time, in the subsequent stage, we re-run the main regression with IMR as an added control variable to mitigate potential self-selection bias. The results are consistent with our earlier findings (Table 2) which is, there is a negative relationship between DLLP and LC. Our self-selection parameter (IMR) is positive and statistically significant, indicating that bank-level characteristics which are related to the DLLP, is positively correlated with LC.

Next, we turn our focus on to the concern of reverse causality by leveraging the instrumental variable (IV) approach (Column 3 for the 1st stage and Column 4 for the 2nd stage in Table 8). We use IV estimation approach to extract the exogenous element of LC to test our endogeneity concern further. We looked for an IV that is correlated with LC yet not correlated with bank level DLLP. The average discretionary loan loss variable of the industry (DLLP_AVG) seems to fit that requirement and as can be observed from the above table, DLLP_AVG is positive and significant with our dependent variable at the one percent significance level. It is worth noting that the second stage coefficients are much larger than the coefficient estimated by the OLS regression in the first stage of the IV process. Since the larger coefficient in the second stage is an indication of potential reverse causality, it is appropriate that we use an IV approach to establish the relationship between EM through DLLP and LC. Given the fact that, the instrumentation process helps to isolate the causal impact of DLLP on LC, the larger coefficients of the IV estimation from the second stage do validate the inverse relationship that we come to find between LC and EM through DLLP in our primary baseline analysis. To strengthen our results from the IV process, we test for the relevancy of our instrument using the Kleibergen-Paap Wald F-Statistic test, which tests for under identification without the independent and identically distributed (iid) of each random variable assumption; we run Cragg-Donald Wald F-Statistic test to test for weak identification and Anderson-Rubin Wald test to test for weak instrument. The Kleibergen-Paap Wald F-Statistic is 94.46 and significant at the one percent level which means our IV is not under identified, the Cragg-Donald Wald F-Statistic (Weak identification test) is 161.78 and significant at the one percent level as well, well above the critical values of Stock and Yogo (2002), which indicates that our instrumental variable is relevant and the Anderson-Rubin Wald test is 41.9 and significant at the one percent level as well, indicating our IV is robust.

Table 8
Endogeneity concerns

	Heckman		IV		PSM			
	1st stage	2nd stage	1st stage	2nd stage	N=1 w/o replacement	N = 1 with replacement	N = 2	N = 3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DLLP		–0.406***		–9.810***	–0.483**	–0.526**	–0.637***	–0.782***
		(0.115)		(0.982)	(0.211)	(0.265)	(0.238)	(0.222)
SIZE	0.025	–0.026**	–0.000	–0.030**	–0.042***	–0.032**	–0.036**	–0.033**
	(0.017)	(0.013)	(0.000)	(0.013)	(0.015)	(0.016)	(0.015)	(0.015)
CAP	2.549***	–0.298**	–0.012***	–0.463***	–0.338**	–0.564***	–0.453***	–0.477***
	(0.564)	(0.120)	(0.004)	(0.124)	(0.146)	(0.164)	(0.155)	(0.153)
EARNINGS	–0.496	1.471***	–0.051***	1.384***	1.546***	1.646***	1.600***	1.644***
	(1.913)	(0.172)	(0.009)	(0.160)	(0.220)	(0.256)	(0.234)	(0.232)
GROWTH	–0.515**	–0.012	–0.001	–0.029**	–0.026	–0.053*	–0.044	–0.038
	(0.235)	(0.014)	(0.001)	(0.015)	(0.020)	(0.030)	(0.027)	(0.025)
NPL	20.846***	–0.709***	0.080***	–0.084	–0.816***	–0.841***	–0.904***	–0.913***
	(0.967)	(0.105)	(0.005)	(0.094)	(0.143)	(0.146)	(0.145)	(0.145)
Z-SCORE	–0.005***	0.000	–0.000***	–0.000	0.000	–0.000	–0.000	–0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SD(EARNINGS)	9.917***	–0.143	–0.010	–0.159	0.102	0.335	0.307	0.311
	(2.304)	(0.252)	(0.011)	(0.244)	(0.347)	(0.376)	(0.347)	(0.332)

(*continue on next page*)

Table 8 (*continued*)

	Heckman		IV		PSM			
	1st stage	2nd stage	1st stage	2nd stage	N=1 w/o replacement	N = 1 with replacement	N = 2	N = 3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DLLP_AVG	41.269***		0.150***					
	(7.590)		(0.031)					
LAMDA		0.005**						
		(0.002)						
Constant	–0.720***	0.843***	0.006	0.948***	1.060***	0.934***	0.975***	0.948***
	(0.227)	(0.178)	(0.004)	(0.181)	(0.202)	(0.222)	(0.201)	(0.203)
Observations	21,480	32,354	34,287	32,879	10,750	5,745	8,051	9,311
R^2	0.098	0.254	0.187	0.257	0.247	0.272	0.259	0.251
# clusters	1729	1,752	1,821	1,756	1,637	1,454	1,550	1,582
BFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Underidentification test Kleibergen-Paap Wald F-Stat				94.460***				
Weak identification test Cragg-Donald Wald F-Stat				161.78***				
Weak instrument robust inference Anderson-Rubin Wald test				41.900***				

Note: Robust standard errors in parentheses, ***, **, * indicate significance at the 1%, 5%, and 10% level respectively.

The last endogeneity test we carry out is the propensity score matching (PSM) procedure to mitigate selection bias. In carrying out the process, we first stratify the banks in the sample according to DLLP behaviour quartiles. Then, using a logit model (similar to the first stage of Heckman selection model), we assess the propensity of a bank engaging the most in EM with the control variables. We also add in this logit model as an IV, the average of EM of the industry (DLLP_AVG). Subsequently, we pair each bank that employs EM the most with another bank that has the closet propensity score. We use 0.0005 caliper to minimise the less than desirable matching risk. We use one-to-one matching without replacement (column 5), which entails each bank to be used only once, as well as one-to-one matching with replacement (column 6), where no matching restriction is applied. To take the PSM further, we also match each bank that engage more earnings management with two and three other banks that have the closest propensity scores. The PSM results are stronger in magnitude and as significant as that of our baseline results that we have gotten earlier. For the most part the results are similar with a few interesting exceptions. The relationship between our variable of interest (DLLP) and LC remains strong and as significant as our main findings.

CONCLUSION

LC is an existential characteristic of banks which the industry has managed to leverage and morph into an edge in competition. Over the last 30 years, LC has become a USD12.3 trillion business and large banks seem to have all but secured their indelible footprint in the banking industry. Moreover, over a 24-year period (1984 through 2008) big banks have managed to turn their 76% dominance to a prodigious 86% footprint, while the medium and small banks lost ground in the wake. So, looking for ways to create liquidity has become an existential crisis for non-large banks also an avenue for larger banks to maintain their leads. In an effort to find an innovative way to create liquidity, banks have turned to tools that lend themselves to be manipulated at discretion without material consequence to the rest of the business. DLLP has become such a tool. We analysed 16 years (from 2000 through 2015) of bank holding company data from the Federal Reserve's Report of Condition and Income Call report and explore the relationship between DLLP and LC and find that, perhaps much to the dismay of some banks, earning manipulation through a tool like DLLP has a negative impact on LC (confirms our null hypothesis, H_0). Moreover, this impact is indiscriminate regardless of whether the banks are facing an economy that is marred by financial crisis or otherwise. We find that smaller, less capitalised banks with low growth and with high non-performing loan on their books tend to engage in EM feature to create liquidity. On the other hand, banks with growth prospects, high profit and higher capital base are less likely to resort to EM to create liquidity. We find that highly profitable banks with lower earnings volatility tend to create more liquidity and banks that manipulate their reported numbers, become more opaque and create less liquidity. The marginal effect of DLLP on LC differ across the quantiles of LC distribution meaning, the impact on the LC appears to be less profound for high liquidity creating banks. Consistent with our economic intuition, the H_0 dominates for the small banks, but not for the medium and large banks. Our findings stand the test of various sensitivity tests to demonstrate their robustness and consistent with prior findings in the literature. In their recent paper, Tran and Ashraf (2018) report that banks that pay dividends are more transparent, DLLP of dividend paying banks are lower and EM behaviour is associate with opacity. They also find that even after controlling for various control measures, banks with growth prospects, high profit and higher capital base are less likely to resort to EM are therefore less opaque. Although, exploring relationship between LC and opacity is beyond the scope of our study, we do however find the same relationship holds between DLLP, growth prospect, profitability and capital base.

APPENDIX A

Variables	Definition
LC	Dollar amount of "catfat" LC normalised by gross total asset. The "catfat" measure classifies loans based on category and includes off-balance sheet activities.
SIZE	The natural logarithm of gross total assets.
CAP	Book value of equity over gross total assets.
GROWTH	Rate of change of gross total assets.
EARNING	Income before taxes, provisions recognised in income over gross total assets.
SD(EARNING)	Standard deviation of pre-managed earnings over the previous 12 quarters (t–11 to t).
Z-SCORE (LN)	A bank measure of financial risk calculated as: LN([Avg.(ROA) + Avg.(Equity/GTA)]/Stdv of ROA); a larger value indicates lower overall bank risk. Means of ROA and Equity/GTA as well as the standard deviation of ROA are computed over the previous 12 quarters (t–11 to t).
DLLPs	Absolute value of residual from: $llp_{it} = dnpl_{it+1} + dnpl_{it} + dnpl_{it-1} + dnpl_{it-2} + alw_{it-1} + cho_{it} + size_{it} + dloan_{it} + csret_{it} + dgdp_{it} + dunemp_{it} + \varepsilon_{it}$
DLLPs_1	Absolute value of residual from: $llp_{it} = dnpl_{it+1} + dnpl_{it} + dnpl_{it-1} + dnpl_{it-2} + size_{it} + dloan_{it} + csret_{it} + dgdp_{it} + dunemp_{it} + \varepsilon_{it}$
DLLPs_2	Absolute value of residual from: $llp_{it} = dnpl_{it+1} + dnpl_{it} + dnpl_{it-1} + dnpl_{it-2} + size_{it} + dloan_{it} + alw_{it-1} + csret_{it} + dgdp_{it} + dunemp_{it} + \varepsilon_{it}$
DLLPs_3	Absolute value of residual from: $llp_{it} = dnpl_{it+1} + dnpl_{it} + dnpl_{it-1} + dnpl_{it-2} + size_{it} + dloan_{it} + cho_{it} + csret_{it} + dgdp_{it} + dunemp_{it} + \varepsilon_{it}$
DRSGL	Absolute value of residual from: $rsgl_{it} = size_{it} + ursgl_{it} + \varepsilon_{it}$
BFE	Bank fixed effects, represented by dummies for each commercial bank.
QFE	Time fixed effects, represented by dummies for each quarter of the sample period.
NPL	Nonperforming assets over the quarter, scaled by total loans at the beginning of the quarter.
dnpl	Change in NPA over the quarter, divided by total loans at the beginning of the quarter.
LOAN	Total loans over the quarter.

Variables	Definition
dloan	Change in total loans over the quarter, divided by total loans at the beginning of the quarter.
alw	Loan loss allowance as a percentage of lagged total loans.
cho	Adjusted charge-off as a percentage of lagged total loans.
rsgl	Realised security gains and losses as a percentage of total assets (includes realised gains and losses from available-for sale securities and held-to-maturity securities).
ursgl	Unrealised security gains and losses (includes only unrealised gains and losses from available-for-sale securities) as a percentage of total assets.
crest	The return on the Case-Shiller Real Estate Index over the quarter.
dunemp	Change in unemployment rates over the quarter.
dgdp	Change in GSP (gross state product) over the quarter.

REFERENCES

Acharya, V. V., & Mora, N. (2015). A crisis of banks as liquidity providers. *The Journal of Finance, 70*, 1–43. https://doi.org/10.1111/jofi.12182

Adhikari, B. K., & Agrawal, A. (2016). Does local religiosity matter for bank risk-taking? *Journal of Corporate Finance, 38*, 272–293. https://doi.org/10.1016/j.jcorpfin.2016.01.009

Agénor, P. R., & Zilberman, R. (2015). Loan loss provisioning rules, procyclicality, and financial volatility. *Journal of Banking & Finance, 61*, 301–315. https://doi.org/10.1016/j.jbankfin.2015.08.035

Alali, F., & Jaggi, B. (2011). Earnings versus capital ratios management: Role of bank types and SFAS 114. *Review of Quantitative Finance and Accounting, 36*(1), 105–132. https://doi.org/10.1007/s11156-010-0173-4

Anandarajan, A., Hasan, I., & McCarthy, C. (2007). Use of loan loss provisions for capital, earnings management and signalling by Australian banks. *Accounting & Finance, 47*(3), 357–379. https://doi.org/10.1111/j.1467-629X.2007.00220.x

Andries, K., Gallemore, J., & Jacob, M. (2017). the effect of corporate taxation on bank transparency: Evidence from loan loss provisions. *Journal of Accounting and Economics, 63*(2–3), 307–328. https://doi.org/10.1016/j.jacceco.2017.03.004

Beatty, A. L., Ke, B., & Petroni, K. R. (2002). Earnings management to avoid earnings declines across publicly and privately held banks. *Accounting Review, 77*, 547–570. https://doi.org/10.2308/accr.2002.77.3.547

Beatty, A., & Harris, D. G. (1999). The effects of taxes, agency costs and information asymmetry on earnings management: A comparison of public and private firms. *Review of Accounting Studies 4*, 299–326. https://doi.org/10.1023/A:1009642403312

Beatty, A., & Liao, S. (2014). Financial accounting in the banking industry: A review of the empirical literature. *Journal of Accounting & Economics 58*, 339–383. https://doi.org/10.1016/j.jacceco.2014.08.009

Berger, A. N. (2010). Financial crises and bank liquidity creation. AFA 2010 Atlanta Meetings Paper. https://doi.org/10.2139/ssrn.1364962

Berger, A. N., & Bouwman, C. H. (2009). Bank liquidity creation. *Review of Financial Studies, 22*, 3779–3837. https://doi.org/10.1093/rfs/hhn104

Berger, A. N., & Bouwman, C. H. (2013). How does capital affect bank performance during financial crises? *Journal of Financial Economics*, *109*(1), 146–176. https://doi.org/10.1016/j.jfineco.2013.02.008

Berger, A. N., & Bouwman, C. H. (2017). Bank liquidity creation, monetary policy, and financial crises. *Journal of Financial Stability 30*, 139–155. https://doi.org/10.1016/j.jfs.2017.05.001

Berger, A. N., El Ghoul, S., Guedhami, O., & Roman, R. A. (2016). Internationalization and bank risk. Federal Reserve Bank of Kansas City Working Paper No. 15-08. https://doi.org/10.2139/ssrn.2661740

Bhattacharya, S., & Thakor, A. (1993). Contemporary banking theory. *Journal of Financial Intermediation 3*, 2–50. https://doi.org/10.1006/jfin.1993.1001

Borio, C., Furfine, C., & Lowe, P. (2001). Procyclicality of the financial system and financial stability: Issues and policy options. *BIS Papers No. 1*, 1–57.

Bouchekoua, A., Matoussi, H., & Trabelsi, S. (2010). *Monolithic versus differential impacts of SOX regulation on market valuation of banks' loan loss provision.* Retrieved from https://ssrn.com/abstract=1762810. https://doi.org/10.2139/ssrn.1664170

Bouvatier, V., Lepetit, L., & Strobel, F. (2014). Bank income smoothing, ownership concentration and the regulatory environment. *Journal of Banking & Finance, 41*, 253–270. https://doi.org/10.1016/j.jbankfin.2013.12.001

Boyd, J., & Prescott, E. E. (1986). Financial intermediary-coalitions. *Journal of Economic Theory, 38*, 211–232. https://doi.org/10.1016/0022-0531(86)90115-8

Bryant, J. (1980). A model of reserves, bank runs, and deposit insurance. *Journal of Banking and Finance, 4*, 335–344. https://doi.org/10.1016/0378-4266(80)90012-6

Bryce, C., Dadoukis, A., Hall, M. N., & Simper, R. (2015). An analysis of loan loss provisioning behaviour in Vietnamese banking. *Finance Research Letters, 14*, 69–75. https://doi.org/10.1016/j.frl.2015.05.014

Bushman, R. M., & Williams, C. D. (2012). Accounting discretion, loan loss provisioning, and discipline of banks' risk-taking. *Journal of Accounting and Economics, 54*, 1–18. https://doi.org/10.1016/j.jacceco.2012.04.002

Chen, C. R., Huang, S. Y., & Zhang, T. (2016). Non-interest income, trading, and bank risk. *Journal of Financial Services Research, 51*(1), 19–53. https://doi.org/10.1007/s10693-015-0235-9

Collins, J. H., Shackelford, D. A., & Wahlen, J. M. (1995). Bank differences in the coordination of regulatory capital, earnings, and taxes. *Journal of Accounting Research, 33*, 263–291. https://doi.org/10.2307/2491488

Curcio, D., & Hasan, I. (2015). Earnings and capital management and signaling: The use of loan-loss provisions by European banks. *The European Journal of Finance, 21*(1), 26–50. https://doi.org/10.1080/1351847X.2012.762408

Dahl, D. (2013). Bank audit practices and loan loss provisioning. *Journal of Banking & Finance, 37*(9), 3577–3584. https://doi.org/10.1016/j.jbankfin.2013.05.007

De Jonghe, O. (2010). Back to the basics in banking? A micro-analysis of banking system stability. *Journal of Financial Intermediation, 19*, 387–417. https://doi.org/10.1016/j.jfi.2009.04.001

Dechow, P. M., & Dichev, I. D. (2002). The quality of accruals and earnings: the role of accrual estimation errors. *The Accounting Review, 77*, 35–59. https://doi.org/10.2308/accr.2002.77.s-1.35

DeYoung, R., & Roland, K. P. (2001). Product mix and earnings volatility at commercial banks: Evidence from a degree of total leverage model. *Journal of Financial Intermediation, 10*, 54–84. https://doi.org/10.1006/jfin.2000.0305

Diamond, D. (1984). Financial intermediation and delegated monitoring. *Review of Economic Studies, 51*, 393–414. https://doi.org/10.2307/2297430

Diamond, D. W., & Dybvig, P. H. (1983). Bank runs, deposit insurance, and liquidity. *Journal of Political Economy*, *91*(3), 401–419. https://doi.org/10.1086/261155

Díaz, V., & Huang, Y. (2017). The role of governance on bank liquidity creation. *Journal of Banking & Finance, 77*, 137–156. https://doi.org/10.1016/j.jbankfin.2017.01.003

Dou, Y., Ryan, S. G., & Zou, Y. (2016). The effect of credit competition on banks' loan loss provisions. *Journal of Financial and Quantitative Analysis, Forthcoming*, https://ssrn.com/abstract=2192586

Doyle, J. T., Weili G, & McVay, S. (2007). Accruals quality and internal control over financial reporting. *The Accounting Review, 82*, 1141–1170. https://doi.org/10.2308/accr.2007.82.5.1141

El Sood, H. A. (2012). Loan loss provisions and income smoothing in US banks pre and post the financial crisis. *International Review of Financial Analysis, 25*, 64–72. https://doi.org/10.1016/j.irfa.2012.06.007

Ellul, A., & Yerramilli, V. (2013). Stronger risk controls, lower risk: Evidence from u.s. bank holding companies. *The Journal of Finance 68*, 1757–1803. https://doi.org/10.1111/jofi.12057

Fidrmue, J., Fungáčová, Z., & Will, L. (2015). Does bank liquidity creation contribute to economic growth? Evidance from Russia. *BOFIT Discussion Paper No. 7/2015*. https://doi.org/10.2139/ssrn.2580182

Fonseca, A., & Gonzàlez, F. (2008). Cross-country determinants of bank income smoothing by managing loan-loss provisions. *Journal of Banking and Finance, 32*(2), 217–228. https://doi.org/10.1016/j.jbankfin.2007.02.012

Foos, D., Norden, L., & Weber, M. (2009). Loan growth and riskiness of banks. *Journal of Banking and Finance, 34*, 2929–2940. https://doi.org/10.1016/j.jbankfin.2010.06.007

Hamadi, M. H. (2016). Does Basel II affect the market valuation of discretionary loan loss provisions? *Journal of Banking & Finance, 70*, 177–192. https://doi.org/10.1016/j.jbankfin.2016.06.002

Heckman, J. J., Ichimura, H., & Todd, P. E. (1997). Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. *The Review of Economic Studies, 64*, 605–654. https://doi.org/10.2307/2971733

Holmstrom, B., & Tirole, J. (1998). Public and private supply of liquidity. *Journal of Political Economy, 106*, 1–40. https://doi.org/10.1086/250001

Kanagaretnam, K., Lim, C. Y., & Lobo, G. J. (2010). Auditor reputation and earnings management: International evidence from the banking industry. *Journal of Banking & Finance, 34*(10), 2318–2327. https://doi.org/10.1016/j.jbankfin.2010.02.020

Kanagaretnam, K., Lobo, G. J., & Yang, D. H. (2005). Determinants of signalling by banks through loan loss provisions. *Journal of Business Research, 58*(3), 312–320. https://doi.org/10.1016/j.jbusres.2003.06.002

Kashyap, A. K., Rajan, R. and Stein, J. C. (2002). Banks as liquidity providers: An explanation for the coexistence of lending and deposit taking. *The Journal of Finance, 57*, 33–73. https://doi.org/10.1111/1540-6261.00415

Kilic, E., Lobo, G. J., Ranasinghe, T., & Sivaramakrishnan, K. (2012). The impact of SFAS 133 on income smoothing by banks through loan loss provisions. *The Accounting Review, 88*(1), 233–260. https://doi.org/10.2308/accr-50264

Klapper, L., Laeven, L., & Rajan, R. (2006). Entry regulation as a barrier to entrepreneurship. *Journal of Financial Economics, 82*, 591–629. https://doi.org/10.1016/j.jfineco.2005.09.006

Klomp, J., & Haan, J. D. (2012). Banking risk and regulation: Does one size fit all? *Journal of Banking & Finance, 36*, 3197–3212. https://doi.org/10.1016/j.jbankfin.2011.10.006

Kwan, S. H. (2004). Risk and return of publicly held versus privately owned banks. *Economic Policy Review, 10*(2). Available at SSRN: https://ssrn.com/abstract=787884

Laeven, L., & Levine, R. (2007). Is there a diversification discount in financial conglomerates? *Journal of Financial Economics, 85*, 331–367. https://doi.org/10.1016/j.jfineco.2005.06.001

Laeven, L., & Levine, R. (2009). Corporate governance, regulation, and bank risk taking. *Journal of Financial Economics 93*, 259–275. Retrieved from SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1142967 https://doi.org/10.1016/j.jfineco.2008.09.003

Laeven, L., & Majnoni, G. (2003). Loan loss provisioning and economic slowdowns: too much, too late? *Journal of Financial Intermediation, 12*(2), 178–197. https://doi.org/10.1016/S1042-9573(03)00016-0

Leventis, S., Dimitropoulos, P. E., & Anandarajan, A. (2011). Loan loss provisions, earnings management and capital management under IFRS: The case of EU commercial banks. *Journal of Financial Services Research, 40*(1–2), 103–122. https://doi.org/10.1007/s10693-010-0096-1

Levine, R., & Zervos, S. (1998). Stock markets, banks, and economic growth. *The American Economic Review, 88*, 537–558. https://doi.org/10.1596/1813-9450-1690

Liu, C., Ryan, S., & Wahlen, J. (1997). Differential valuation implications of loan loss provisions across banks and fiscal quarters. *The Accounting Review, 72*, 133–146.

Lobo, G. J., & Yang, D. H. (2001). Bank managers' heterogeneous decisions on discretionary loan loss provisions. *Review of Quantitative Finance and Accounting, 16*(3), 223–250. https://doi.org/10.1023/A:1011284303517

Marton, J., & Runesson, E. (2017). The predictive ability of loan loss provisions in banks: Effects of accounting standards, enforcement and incentives. *The British Accounting Review, 49*(2), 162–180. https://doi.org/10.1016/j.bar.2016.09.003

Pain, D. (2003). The provisioning experience of the major UK banks: A small panel investigation. Bank of England working paper no. 177. Available at SSRN: https://ssrn.com/abstract=425760 or https://doi.org/10.2139/ssrn.425760

Perez, D., Salas-Fumas, V., & Saurina, J. (2008). Earnings and capital management in alternative loan loss provision regulatory regimes. *European Accounting Review, 17*(3), 423–445. https://doi.org/10.1080/09638180802016742

Peterson, K. O. (2015). Loan loss provisioning, income smoothing, signalling, capital management and procyclicality: Does IFRS matter? Empirical evidence from Nigeria. *Mediterranean Journal of Social Science, 6*(2), 224–232.

Peterson, K. O. (2017a). Bank earnings smoothing, audit quality and procyclicality in Africa: The case of loan loss provisions. *Review of Accounting and Finance, 16*(2), 142–161. https://doi.org/10.1108/RAF-12-2015-0188

Peterson, K. O. (2017b). Discretionary provisioning practices among Western European banks. *Journal of Financial Economic Policy, 9*(1), 109–118. https://doi.org/10.1108/JFEP-07-2016-0049

Ramakrishnan, R. T., & Thakor, A. (1984). Information reliability and a theory of financial intermediation. *Review of Economics Studies, 51*, 415–432. https://doi.org/10.2307/2297431

Ryan, S. G., & Keeley, J. H. (2013). Discussion of "Did the SEC impact banks' loan loss reserve policies and their informativeness?". *Journal of Accounting and Economics, 56*(2), 66–78. https://doi.org/10.1016/j.jacceco.2013.10.006

Saurina, J. (2009). *Dynamic provisioning: The experience of Spain.* Washington DC: World Bank.

Scholes, M. S., Wilson, P. G., & Wolfson, M. A. (1990). Tax planning, regulatory capital planning, and financial reporting strategy for commercial banks. *Review of financial Studies, 3*, 625–650. https://doi.org/10.1093/rfs/3.4.625

SelectUSA.gov. (2017). *Financial services spotlight, the financial services industry in the United States.* SelectUSA.gov, prepared in collaboration with the International Trade Administration's Industry & Analysis Unit (I&A). Retrieved from https://www.selectusa.gov/financial-services-industry-united-states

Stiroh, K. J., & Rumble, A. (2006). The dark side of diversification: The case of US financial holding companies. *Journal of Banking & Finance, 30*, 2131–2161. https://doi.org/10.1016/j.jbankfin.2005.04.030

Stock, J. H., & Yogo, M. (2002). Testing for weak instruments in Linear IV Regression. Working Paper, National Bureau of Economic Research. https://doi.org/10.3386/t0284

Tran, D. V., & Ashraf, B. N. (2018). Dividend policy and bank opacity. *International Journal of Financal Economics*, *23*(2), 1–19. https://doi.org/10.1002/ijfe.1611

Tran, D., Hassan, M. K., & Houston, R. (2018). Discretionary loan-loss provision behavior in the US banking industry. *Networks Financial Institute Working Paper 2018-WP-01*, 1. https://doi.org/10.2139/ssrn.3118012

Tran, D. V., Hassan, M. K., & Houston, R. (2019). Activity strategies, information asymmetry, and bank opacity. *Economic Modelling, 83*, 160–172. https://doi.org/10.1016/j.econmod.2019.02.008

Tran, D. V. (2019). Activity strategies. agency problems and bank risk. SSRN Scholarly Paper. Rochester, New York.

Wahlen, J. (1994). The nature of information in commercial bank loan loss disclosures. *The Accounting Review, 69*, 455–478.

Wezel, T., Chan Lau, J. A., & Columba, F. (2012). Dynamic loan loss provisioning: Simulations on effectiveness and guide to implementation. *IMF Working Paper, WP/12/110*. https://doi.org/10.2139/ssrn.2055716

Wong, E., Fong, T., & Choi, H. (2011). Procyclicality of loan-loss provisioning and systemic risk in the Hong Kong banking system. *Hong Kong Monetary Authority Quarterly Bulletin*, 1.