Liquidity Provision and Bank Opacity

Saeyeon Oh and Junho Park*

Abstract

This study examines the relationship between banks' liquidity provision and opacity, measured with discretionary loan loss provisions. Banks, particularly those with significant unused commitments before the crisis, increased discretionary loan loss provisions at the onset of the 2007-2009 Global Financial Crisis. Our results provide empirical evidence supporting the theoretical literature on the relationship between liquidity provisions and bank opacity.

JEL classification: G01, G21
Keywords: Global Financial Crisis, bank opacity, liquidity provision, discretionary loan loss provision

*Saeyeon Oh (first author, saeyeonoh@bok.or.kr) is at the Bank of Korea and Junho Park (corresponding author, junhopark@mju.ac.kr) is at Myongji University. We thank helpful comments from Sumit Agarwal, Hyun-Soo Choi, Sudipto Dasgupta, Yongtae Kim, Chang Joo Lee, Ajay Palvia, Jungsoo Park, Kwangwoo Park, Tram Vu, Chamna Yoon, and conference participants at 2022 Financial Management Association (FMA) Annual Meeting and 2022 FMA Asia/Pacific Conference. The opinions expressed in this article are the authors' own and do not reflect the view of the Bank of Korea.

1. Introduction

Banks are unique in their ability to transform short-term liquid deposits into long-term illiquid loans. Contrary to non-financial firms, banks' primary funding source is liquid deposits from not only informed investors, but also uninformed investors. Thus, if banks fully disclose their difficulties, uninformed investors are likely to withdraw their deposits, concerned with the loss from the game with informed investors. As a result, banks have an incentive to obfuscate their financial reports.

This study investigates the relationship between banks' liquidity provision and their opacity. To this end, we particularly pay attention to the banks at the onset of the 2007-2009 Global Financial Crisis (GFC), in which they experienced difficulties providing liquidity due to a sudden rise in borrowers' credit needs. Since the crisis originated in the banking sector, investors' confidence in the quality of banks' financial reports plummeted. In the meantime, firms drew down bank funds heavily from existing commitments in response to the liquidity shock during the crisis. This situation led the banks, particularly those with more commitments, to take immediate action to make investors be reassured that banks' assets are safe by hiding adverse information from their balance sheets.

We use the commitments before the onset of the crisis to gauge the liquidity provision level. Since most banks could not have predicted the crisis, it is unlikely that they have chosen the degree of liquidity provision considering the crisis ex-ante. We conduct a difference-in-differences analysis on the bank opacity, measured with discretionary loan loss provisions (DLLPs), by comparing banks with large and small commitments before the crisis. More DLLPs indicate higher bank opacity as they hinder outsiders from valuing the bank's fundamentals.

We find that banks with more commitments before the crisis are associated with more DLLPs after the onset of the crisis. Specifically, banks with commitments above the median before the crisis have increased DLLPs approximately twenty percent more after the onset of the crisis than those with commitments below the median. Our results are also robust to various model specifications, such as propensity score matching. Furthermore, the trends in both loan commitments and DLLPs, as well as Granger causality tests, suggest that the changes in DLLPs are only significant after the onset of the crisis, alleviating endogeneity concerns.

We further examine whether the treatment effect varies across banks. Bank opacity is more critical for low-quality banks than high-quality banks since informed investors would not withdraw from high-quality banks even in a crisis. Consistent with this prediction, the increase in DLLPs is almost two times larger for low-quality than high-quality banks. In addition, the opacity of banks with more senior depositors is less compromised than those with less senior depositors at the onset of the crisis. This difference originates from the seniors' inelastic deposit supply. Lastly, the association between liquidity provision and bank opacity is less significant in large and public banks, implying that they face regulatory scrutiny requiring high transparency.

Related Literature This study relates to the literature on the liquidity provision of banks during distress. Ivashina and Scharfstein (2010) explain that during the panic in the 2007 financial crisis, outstanding commercial and industrial loan amounts increased, contrary to the dramatic decline in syndicated lending volumes. This discrepancy arose from the large credit drawdowns from the existing credit lines. Acharya and Mora (2015) show that, due to the sudden increase in the drawdowns, banks had a hard time honoring the commitments and extending new loans as the deposit inflow to the banks was weak. They demonstrate that growth in deposits and credit extensions were lower, and loan-to-deposit shortfalls were wider for banks with large unused commitments, especially during the first year of the crisis. Banks' provision of liquidity via existing credit lines during distress is not limited to the 2007 financial crisis. Recent papers on the COVID-19 pandemic also observe a similar pattern (Kapan and Minoiu, 2021; Li et al., 2020). This study contributes to the literature by examining banks' reactions to unexpected large credit drawdowns in adjusting opacity.

This paper also resonates with the literature on the benefit of bank opacity. While bank transparency can enhance financial stability by improving ex-ante market discipline on banks (Nier, 2005; Granja, 2018), it can have ex-post destabilizing effects (Cordella and Yeyati, 1998; Furman and Stiglitz, 1998).[1] Transparent information disclosure makes investors respond sensitively to the information, which sometimes aggravates banks' originally temporary and manageable problems. Dang et al. (2017) and Holmstrom (2015) provide a similar view and highlight the benefit of banks being "secret keepers." When bank debts become information-sensitive, it is costly for banks to respond to the investors' questions and requests, harming liquidity provision. On the other hand, opacity on the bank asset quality lets investors stay homogeneously uninformed, preventing the harm. Morris and Shin (2002) is a reference for the effect of public information in a more generalized setting. They provide the example of Australia changing from monthly to quarterly reporting on the balance of trade figures due to the destabilizing effect of public information. This paper provides relevant empirical findings in banks. Banks endogenously determine financial reporting opacity by comparing the costs and benefits of the information disclosure, and a considerable benefit is in the efficient liquidity provision.

Two closely related papers that share the theoretical background are Pérignon et al. (2018), and Jiang et al. (2019). Pérignon et al. (2018) investigate the relationship between wholesale fund dry-ups and bank performance in the European certificates of deposit market. By showing that funding dry-ups predict a future decline in performance, they provide supporting evidence for heterogeneous information among investors, which makes opacity beneficial for banks. Their results support the views of Gorton and Pennacchi (1990), Dang et al. (2017), and Calomiris and Kahn (1991). While sharing the same theoretical background, this study focuses more on the change in bank opacity per se, using discretionary provisions as the outcome variable.

On the other hand, Jiang et al. (2019) study the effect of deposit windfalls on bank transparency using shale gas development as a natural experiment. They show that the

[1] See Acharya and Ryan (2016), and Nier (2005) for the debate on bank opacity and financial stability.

shale boom-exposed banks facing an exogenous increase in deposit supply reduced information disclosure, as predicted by the adverse selection models of Akerlof (1970) and Myers and Majluf (1984). The opposite effect of external financing on bank opacity observed in this study does not contradict but complements the findings of Jiang et al. (2019). Jiang et al. (2019) focus on the variation in deposit supply during normal periods when bank debts remained information-insensitive, while this paper's interest is in the variation in deposit demand during distress when bank debts became information-sensitive.

Finally, this study extends the growing literature on the determinants of bank opacity. Banks compromise financial reporting quality to manage earnings or regulatory capital (Beatty and Liao, 2014; Kim and Kross, 1998). Studies have assessed the efficacy of corporate governance and regulatory oversight in restraining such activities (Cornett et al., 2009; Dal Maso et al., 2018). Similarly, market competition also affects financial reporting quality by facilitating bank monitoring (Jiang et al., 2016). This study contributes to the literature by examining how the unique role of banks in providing liquidity affects opacity.

The remainder of this paper proceeds as follows: Section 2 explains the identification strategy and the regression model. Section 3 describes the data. The empirical results are presented and discussed in Section 4. Section 5 concludes.

2. Methodology

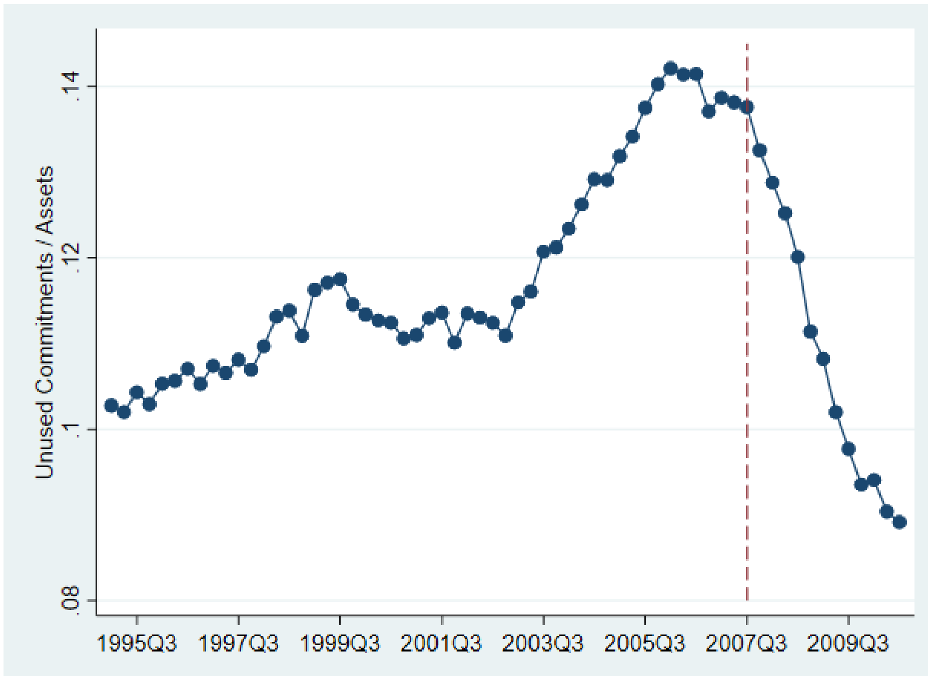
2.1. Identification Strategy

Banks make various commitment contracts, including loan commitments, letters of credit, and securities underwriting. Most commercial and industrial (C&I) loans are made under commitment. According to the Survey of Terms of Business Lending, 77.4% of all C&I loans were made under loan commitment contracts in February 2007. This percentage increased to 81.7% in May 2017.

Figure 1 depicts the trend of average unused commitments relative to the total assets

Figure 1: Unused commitments to assets ratio

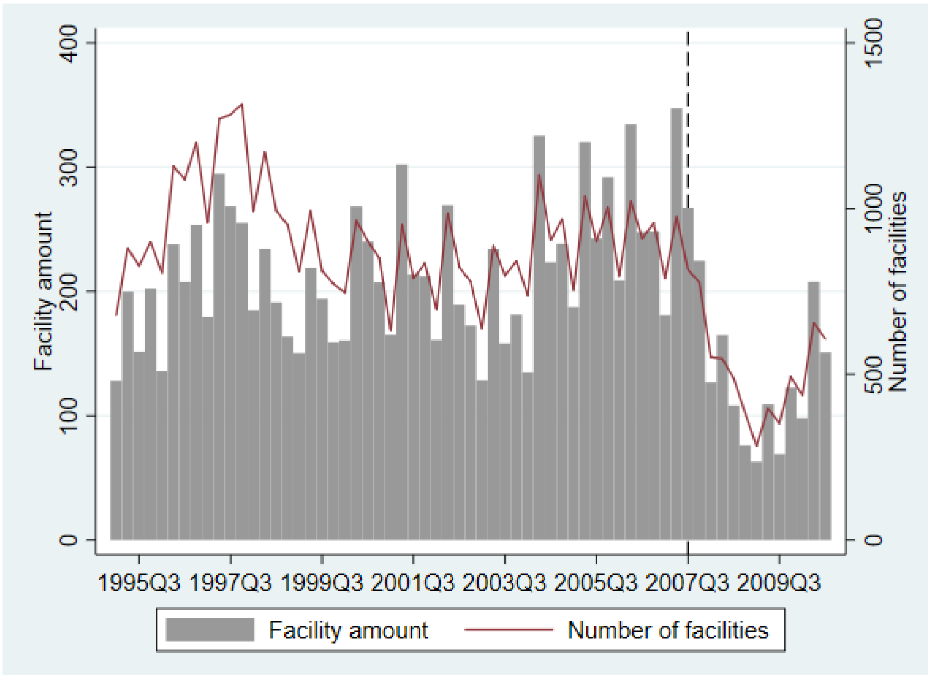
The figure plots the time series of the average unused commitments to assets (UCA) ratio of banks. Unused commitments include the unused amount of loan commitments, letters of credit, securities underwriting, and other commitments. The dashed line indicates 2007Q3, the onset of the financial crisis.



(UCA) of commercial banks in the United States. The dashed line indicates 2007Q3, the onset of the 2007-2009 financial crisis. The fraction of unused commitments steeply diminished starting from this period and did not recover until a few quarters after the crisis. This decline reflects two factors: 1) firms drew funds heavily from the existing lines of credit during the crisis (Ivashina and Scharfstein, 2010; Campello et al., 2011), and 2) banks were reluctant to make new commitments in times of uncertainty. Figure 2 shows the contraction of the new credit line extension during the crisis. The number and amount of new facilities in the form of credit lines reported in the Dealscan database declined sharply during this period. This contraction is partly attributable to the weak deposit flow into the banking system. In the early period of the crisis, bank deposits were not considered safe by investors, and it took explicit government support to regain confidence in the safety of the deposits (Acharya and Mora, 2015).

Figure 2: New credit lines

This figure plots the amount and the number of new credit lines issued in the United States. The facility data is from Dealscan. The dashed line indicates 2007Q3, the onset of the financial crisis.



Given the weak deposit supply, banks with a greater amount of unused commitments encountered more difficulties in providing liquidity. They had to honor the existing credit lines by supplying loans up to the prespecified amount or stand ready to supply the amount at any time. Therefore, the amount of pre-crisis unused commitments generated a variation in difficulties of providing liquidity after the onset of the crisis, which was not fully controllable by banks. As the crisis was unexpected, it is unlikely that the banks made commitments considering the possibility of the crisis any more than usual. The constant increase in unused commitments before the crisis (Figure 1) indicates that most banks could not predict the timing and depth of the crisis. In addition, once loan commitments are made, when and how much to draw down are up to the borrowers, not the banks. Based on these arguments, we conduct a difference-in-differences analysis comparing the changes in financial reporting opacity of banks with large and small amounts of unused commitments before the crisis.

This empirical strategy has a caveat that banks with large and small amounts of unused

Table 1: Banks with large and small amounts of unused commitments

This table compares banks with large and small amounts of unused commitments in 2007Q1. Banks with large unused commitments (denoted as *HighUCA* banks) are the ones with above−median unused commitments to assets ratios (UCA). All continuous variables are winsorized at the 1st and 99th percentiles. The appendix provides detailed definitions of the variables.

	HighUCA banks (1,815 observations)			Control banks (1,815 observations)		
variable	Median	Mean	Std. Dev.	Median	Mean	Std. Dev.
$Assets(\$Mil.)$	334.063	1,494.787	4,913.849	188.384	404.324	1,653.956
CAP	0.093	0.100	0.028	0.096	0.103	0.030
$EBTP$	0.006	0.006	0.003	0.006	0.007	0.004
$Reloans$	0.756	0.724	0.160	0.743	0.719	0.157
$Ciloans$	0.155	0.172	0.098	0.118	0.134	0.084
$Persloans$	0.029	0.045	0.052	0.063	0.085	0.076
NPL	0.004	0.007	0.009	0.006	0.009	0.010
Dep	0.830	0.816	0.077	0.847	0.830	0.076
$Wholesalefunding$	0.231	0.241	0.103	0.216	0.228	0.107

commitments are different in many aspects, especially in their size. Table 1 compares the banks with UCA above and below the sample median in 2007Q1, two quarters before the onset of the crisis. Banks with UCA above the sample median (hereafter *HighUCA* banks) have about 1.8 times larger median and 3.7 times larger mean value of assets. Consistent with the difference in size, *HighUCA* banks lend more to commercial and industrial borrowers and less to individuals and depend more on wholesale funding than the control banks. It is essential to factor in these different characteristics in the empirical analysis to attribute the difference-in-differences in financial reporting opacity between the *HighUCA* and control banks to liquidity provision difficulties. With this caveat in mind, we control various bank characteristics and bank fixed effects in the diff-in-diff regression model described in the next section. In addition, we conduct propensity score matching to compose a sample of banks with the most similar traits and see how it affects the result.

2.2. The Difference-in-differences Approach

We define *HighUCA* banks with *UCA* higher than the sample median in 2007Q1 as treated banks that were more subject to challenges in liquidity provision after the onset of the crisis.[2] Using the difference-in-differences approach, the change in financial reporting opacity of *HighUCA* banks is compared to that of the control banks. The regression model is as follows:

$$lnDLLP_{i,t} = \beta HighUCA_i \times Post_t + \gamma X_{i,t-1} + \alpha_i + \delta_t + u_{i,t} \tag{1}$$

i and t indicate bank and quarter, respectively. *HighUCA* equals one if the bank reported above-median *UCA* in 2007Q1, and zero otherwise. *Post* equals one for the quarters 2007Q3 and after, and zero otherwise. The bank fixed effects (α_i) and quarter fixed effects (δ_t) complete the difference-in-differences setting, and absorb the effects of time-invariant bank heterogeneity and macroeconomic shocks that affect all banks universally. we also control for bank characteristics, including size, capital ratio, profitability, and loan portfolio variables. Appendix Table A.1 presents the detailed definitions of the variables used in the analysis.

The outcome variable, denoted as *lnDLLP*, is the natural logarithm of DLLPs (*DLLP*). It is one of the most commonly used measures of banks' financial reporting quality (Beatty and Liao, 2014; Kim and Kross, 1998; Kanagaretnam et al., 2010; Jiang et al., 2016; Fan et al., 2020; Delis et al., 2018; Fonseca and González, 2008). There are several reasons why DLLPs serve as a suitable measure to study the topic of this paper. First, discretionary provisions can be estimated for most banks as long as they provide financial reports to the public. On the contrary, other measures based on earnings guidance or 10-K filings are not available for small banks and private banks that are more likely to face external financing constraints. Second, loan loss provisions are banks' estimates on loan losses. It conveys direct information on banks' asset value which should be kept secret to produce liquidity (Dang et al., 2017).

[2] We use *UCA* values two quarters before the onset of the crisis (2007Q3) to determine the treatment status considering the possibility that some of the banks predicted the crisis in advance. However, this is a precautionary measure, and we demonstrate in Section 4 that there were no significant differences in the measure of opacity between the treated and control banks before the crisis.

We estimate the discretionary portion of the loan loss provisions using the following model from Beatty and Liao (2014):

$$\begin{aligned}LLP_{i,s,t} = \alpha_0 + \alpha_1 dNPL_{i,s,t+1} + \alpha_2 dNPL_{i,s,t} + \alpha_3 dNPL_{i,s,t-1} + \alpha_4 dNPL_{i,s,t-2} \\ + \alpha_5 Size_{i,s,t-1} + \alpha_6 LoanGrowth_{i,s,t} + \alpha_7 ALW_{i,s,t-1} + \alpha_8 NCO_{i,s,t} \\ + \alpha_9 GDP_t + \alpha_{10} CSRET_t + \alpha_{11} dUNEMP_{s,t} + \epsilon_{i,s,t}\end{aligned} \tag{2}$$

i, s, and t indicate bank, state of the bank's location, and quarter, respectively. LLP is the loan loss provisions divided by lagged loans. The regressors are change in non-performing loans, size, loan growth, loan loss allowances, net charge-offs, GDP, return on the Case Shiller real estate index, and change in the state unemployment rate. We define the absolute value of the residuals estimated with the model as discretionary provisions ($DLLP$). The intuition is that the amount of LLP explained by the changes in variables on the right-hand side is necessary to cover loan losses. Any positive or negative deviation from the amount is considered discretionary.

A higher value of $DLLP$ indicates higher opacity in financial reports. Therefore, the positive estimate of β in Model (1) implies that banks with a large amount of pre-crisis unused commitments increased opacity more than the control banks. This aligns with theories highlighting the role of banks as liquidity providers (Gorton and Pennacchi, 1990; Dang et al., 2017). In contrast, negative β aligns with the hypothesis that high-quality banks improve transparency to signal their quality to outside investors and attract funds.

3. Data

The sample consists of 68,923 commercial bank-quarter observations. The sample period ranges from 2005Q1 to 2010Q1, from 10 quarters before to 10 quarters after the onset of the crisis in 2007Q3. The primary data source is Call Reports, Reports of Condition and

Income, downloaded via WRDS. The Case-Shiller home price index, GDP per capita, and unemployment rate data are from S&P Dow Jones Indices LLC, U.S. Bureau of Economic Analysis, and U.S. Bureau of Labor Statistics, respectively, and retrieved from FRED, Federal Reserve Bank of St. Louis. We use bank branch locations and deposit information to calculate the Herfindahl Indices. The branch location and deposit data are from Summary of Deposits (SOD). Following Acharya and Mora (2015) and Chen et al. (2019), we exclude banks whose assets grew more than 10% within a quarter and small banks with asset sizes below 100 million dollars. Banks should have at least one observation before and after the treatment (i.e., the onset of the crisis) to be included in the sample. All continuous variables are winsorized at the 1st and 99th percentiles.

Table 2 presents the summary statistics of the variables used in the analysis. The size of loan loss provisions an average bank accrued is 0.18% of loans from the last quarter. The mean and median of the ratio of *DLLP* over *LLP* are 1.23 and 0.53, respectively. The standard deviation is 16.77, which implies that there is substantial variation in the ways banks accrue *LLP*.

Figure 3 depicts the trend in *UCA* for the *HighUCA* banks and control banks. The *HighUCA* banks experienced a significant decrease in *UCA* during the crisis. The control banks' *UCA* also diminished in the post-treatment period, but the relative size of the decrease was much smaller. The difference in the change of *UCA* between the treated and control banks implies that the *HighUCA* banks were more reluctant to make new commitments, or borrowers with existing credit lines drew funds heavily from the credit lines, or both. In either case, this difference supports the empirical strategy of using pre-crisis *UCA* as a source of variation in difficulties in providing liquidity after the onset of the crisis.

Table 3 compares the average value of *lnDLLP* for the *HighUCA* banks and control banks before and after the treatment. *DLLP* increased for both treated and control banks after the onset of the crisis. As the crisis accompanied a great deal of uncertainty, banks could

Table 2: Summary statistics

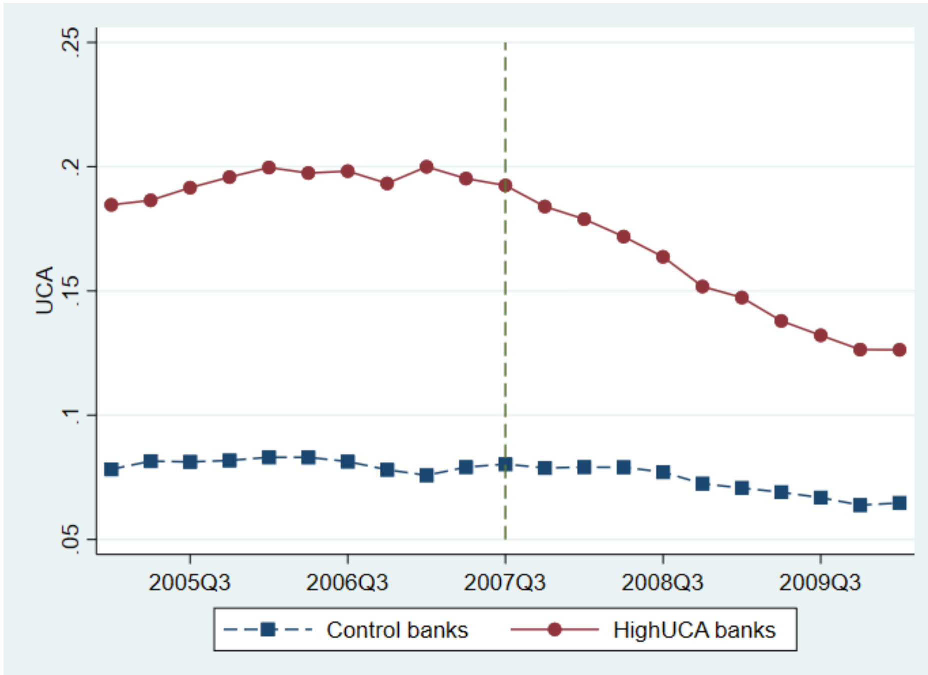
This table displays summary statistics of the sample. The unit of observation is a bank-quarter pair. The sample period is from 2005Q1 to 2010Q1. Unused commitments to assets ratios (UCA) are measured at the end of 2007Q1. All continuous variables are winsorized at the 1st and 99th percentiles. The appendix provides detailed definitions of the variables used in the analysis.

Variable	Obs	Mean	Std. Dev.	P25	P50	P75
$lnDLLP$	68,923	-7.681	1.347	-8.393	-7.602	-6.868
$UCA(2007Q1)$	68,923	.136	.081	.08	.123	.176
$LLP(\%)$	68,923	.177	.381	.024	.064	.151
$dNPL(\%)$	68,923	.149	.813	-.118	.012	.282
$Size$	68,923	12.698	1.02	11.983	12.429	13.1
$LoanGrowth$	68,923	.015	.038	-.008	.013	.036
$GDP(\%)$	68,923	.021	.784	-.103	.246	.38
$CSRET(\%)$	68,923	-.497	2.54	-2.1	-.527	1.408
$dUNEMP(\%p)$	68,923	.196	.524	-.1	.1	.4
ALW_{t-1}	68,923	.014	.006	.01	.012	.015
NCO	68,923	.001	.003	0	0	.001
CAP_{t-1}	68,923	.099	.027	.082	.093	.109
$LOSS_{t-1}$	68,923	.099	.299	0	0	0
$EBTP_{t-1}$	68,923	.006	.005	.004	.006	.008
$Reloans_{t-1}$	68,923	.724	.155	.644	.751	.834
$Ciloans_{t-1}$	68,923	.15	.093	.085	.133	.195
$Persloans_{t-1}$	68,923	.065	.068	.019	.044	.085
HHI_{t-1}	68,923	.204	.109	.127	.181	.253
$Drawdown$	68,923	-.001	.02	-.009	0	.009
$dDep$	68,923	.011	.035	-.01	.01	.032
$NetDrawdown$	68,923	-.011	.042	-.036	-.01	.014
$dCredit$	68,923	.011	.035	-.009	.008	.028
NPL_{t-1}	68,923	.014	.02	.003	.008	.017
$Wholesalefunding_{t-1}$	68,923	.24	.105	.165	.229	.299

have made more discretionary decisions on loan loss provisioning. It is important to note that *HighUCA* banks increased discretionary provisioning significantly more than the control banks. *lnDLLP* increased by 0.608 for the control group, which corresponds to the 83 percent (exp(-7.458)/exp(-8.065)-1) increase in *DLLP*. The change in *lnDLLP* for the *HighUCA* banks was 0.862. This corresponds to a 137 percent (exp(-7.208)/exp(-8.070)-1) increase in *DLLP*, which is significantly larger than that of the control banks.

Figure 3: Unused commitments of the *HighUCA* banks and the control banks

This figure plots the trend of unused commitments to assets ratio (UCA) of the $HighUCA$ banks and the control banks. $HighUCA$ (control) banks are the banks with UCA above (below) the sample median in 2007Q1.



4. Empirical Results

4.1. Pre-crisis Unused Commitments and Difficulties in Liquidity Provision

Before we present the baseline regression results on the relationship between difficulties in liquidity provision and discretionary provisioning, we first check the validity of the empirical strategy described in Section 2.1. In this section, we show that banks with high pre-crisis unused commitments had larger credit drawdowns after the onset of the crisis, but their deposit funding was not sufficient to support credit needs. The funding shortage led to a relative decrease in credit extension by the $HighUCA$ banks.

In particular, the following model is estimated:

$$Y_{i,t} = \beta HighUCA_i \times Post_t + \gamma X_{i,t-1} + \alpha_i + \delta_t + u_{i,t} \tag{3}$$

Table 3: Comparison of means: *lnDLLP* of the *HighUCA* banks and the control banks

This table compares the sample means of *lnDLLP* before and after the onset of the 2007 financial crisis of the *HighUCA* and the control banks. *lnDLLP* is the natural logarithm of the discretionary loan loss provisions (*DLLP*). *DLLP* is the amount of loan loss provisions that are accounted excessively more or less than the necessary amount to cover loan losses. Model (2) estimates *DLLP*. *HighUCA* (control) banks are banks with *UCA* above (below) the sample median in 2007Q1. P-values reported in parentheses are associated with the t-test comparing the means.

	Pre	Post	Diff. (p-value)
HighUCA banks (treated)	-8.070	-7.208	0.862
			(0.000)
Control banks	-8.065	-7.458	0.608
			(0.000)
Diff.	-0.004	0.250	0.254
			(0.000)

$HighUCA_i$ and $Post_t$ are defined as in Section 2.2. $Y_{i,t}$ captures the extent to which banks experienced difficulties in liquidity provision, and we use four variables: $Drawdown$, $\Delta Deposits$, $NetDrawdown$, and $\Delta Credit$. First, following Acharya et al. (2021), we define $Drawdown$ as the decrease in unused commitments ($-1\times$ change in unused commitments) scaled by lagged assets. This variable measures the realized credit drawdowns that banks had to honor. It also reflects the change in banks' new commitments and, thus, is partly endogenously determined. The second dependent variable is $\Delta Deposits$, which is the quarterly change in deposits divided by lagged assets. $NetDrawdown$ is $Drawdown$ minus $\Delta Deposits$, which measures funding constraints of banks. Finally, $\Delta Credit$ is defined as the quarterly change in the credit amount (sum of the loans and unused commitments) extended by the banks. All models include bank fixed effects and quarter fixed effects. The amount of nonperforming loans (NPL), capital ratio (CAP), wholesale funding ($Wholesalefunding$), size ($Size$), and real estate loans ($Reloans$) are controlled following Acharya and Mora (2015), and Chen et al. (2019).

Table 4 presents the results. $HighUCA \times Post$ enters positively in Column 1, showing that banks that had larger unused commitments before the crisis faced higher credit line drawdowns

Table 4: Pre-crisis unused commitments and difficulties in liquidity provision

This table examines the relationship between pre-crisis unused commitments and difficulties in liquidity provision after the onset of the 2007 financial crisis. *Drawdown* is defined as the decrease in unused commitments (unused commitments in $t-1$ minus unused commitments in t) divided by lagged assets. $\Delta Deposits$ equals the change in deposits divided by lagged assets. $NetDrawdown$ is $Drawdown$ minus $\Delta Deposits$. $\Delta Credit$ equals the change in the sum of loans and unused commitments divided by lagged assets. $HighUCA$ is a dummy variable set to one for banks with UCA higher than the sample median in 2007Q1. *Post* equals one for the quarters 2007Q3 and after. Standard errors are clustered at the bank level. The t-statistics are reported in parentheses. ***, **, and * indicate 1%, 5%, and 10% significance, respectively.

VARIABLES	(1) $Drawdown$	(2) $\Delta Deposits$	(3) $NetDrawdown$	(4) $\Delta Credit$
$HighUCA \times Post$	0.007***	-0.001**	0.009***	-0.012***
	(26.998)	(-2.447)	(11.979)	(-19.857)
NPL_{t-1}	0.068***	-0.177***	0.244***	-0.458***
	(12.231)	(-14.215)	(16.750)	(-32.172)
CAP_{t-1}	-0.013*	0.298***	-0.317***	0.085***
	(-1.701)	(15.878)	(-14.851)	(4.756)
$Wholesalefunding_{t-1}$	0.005**	0.102***	-0.101***	-0.015***
	(2.360)	(19.577)	(-17.681)	(-3.392)
$Size_{t-1}$	0.009***	-0.036***	0.046***	-0.028***
	(12.233)	(-16.981)	(17.502)	(-14.009)
$Reloans_{t-1}$	0.015***	-0.015***	0.031***	-0.003
	(6.758)	(-3.148)	(5.330)	(-0.620)
Bank FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Observations	68,923	68,923	68,923	68,923
Adjusted R-squared	0.031	0.110	0.112	0.238

after the onset of the crisis. Column 2 shows that deposit inflows to the $HighUCA$ banks were weaker than the control banks, which exacerbated the funding constraints (Column 3). $HighUCA$ banks faced 0.9 percentage points higher credit drawdowns net of deposit inflows, which corresponds to a 0.21 standard deviation increase in $NetDrawdown$. The result presented in Column 4 suggests that the funding constraints led to a reduction in the overall credit extension by the $HighUCA$ banks. The change in credit extension of the $HighUCA$ banks was lower by 1.2 percentage points, which is as large as the average credit growth during the sample period. These results align with the analyses in Ivashina and Scharfstein (2010), Campello et al. (2011), and Acharya and Mora (2015), and support the identification strategy.

4.2. Baseline Results

Table 5: Difficulties in providing liquidity and discretionary loan loss provisions

This table estimates the relationship between difficulties in providing liquidity and discretionary provisioning. The dependent variable is *lnDLLP*, which is the natural logarithm of discretionary loan loss provisions estimated using Model (2). *HighUCA* is a dummy variable set to one for the banks with *UCA* higher than the sample median in 2007Q1. *Post* equals one for the quarters 2007Q3 and after. Standard errors are clustered at the bank level. The t-statistics are reported in parentheses. ***, **, and * indicate 1%, 5%, and 10% significance, respectively.

VARIABLES	(1) $lnDLLP$	(2) $lnDLLP$	(3) $lnDLLP$	(4) $lnDLLP$	(5) $lnDLLP$ Matching
$HighUCA \times Post$	0.250***	0.209***	0.206***	0.187***	0.239***
	(9.300)	(8.068)	(7.952)	(7.382)	(5.353)
$Size$		-0.071	-0.070	-0.054	-0.159
		(-1.307)	(-1.290)	(-1.023)	(-1.426)
CAP_{t-1}		-0.025	-0.031	0.996*	-0.006
		(-0.043)	(-0.053)	(1.749)	(-0.006)
$LOSS_{t-1}$		0.445***	0.444***	0.236***	0.495***
		(18.802)	(18.754)	(8.876)	(11.269)
$EBTP_{t-1}$		-5.584***	-5.599***	-7.318***	-0.426
		(-2.713)	(-2.715)	(-3.584)	(-0.085)
HHI_{t-1}		-0.450*	-0.451*	-0.467*	-0.529
		(-1.814)	(-1.821)	(-1.947)	(-1.223)
$Reloans_{t-1}$			0.015	0.060	0.159
			(0.051)	(0.213)	(0.301)
$Ciloans_{t-1}$			0.235	0.266	0.324
			(0.707)	(0.825)	(0.508)
$Persloans_{t-1}$			0.934**	0.911**	2.061**
			(1.996)	(2.001)	(2.461)
LLP_{t-1}				33.263***	
				(15.485)	
Bank FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	68,923	68,923	68,923	68,923	28,463
Adjusted R-squared	0.214	0.222	0.222	0.226	0.214

This section presents the estimation results of Model (1) to evaluate the impact of difficulties in liquidity provision on the financial reporting opacity of banks. The regression results presented in Table 5 indicate that *HighUCA* banks reduced financial reporting quality significantly more than control banks after the onset of the crisis. In Column 1, without control variables, the increase in *DLLP* for the *HighUCA* banks was 25 percent higher than that of the control banks. This corresponds to an 11 percent ($0.25\times$ 0.438) increase in discretionary provisioning in response to a one standard deviation increase in $HighUCA \times Post$, which is economically significant. This result aligns with the theoretical prediction that keeping opacity on the loan portfolio can help banks provide liquidity to the market (Dang et al., 2017).

Size, capital ratio, the indicator for negative net income, profitability, and market competition are controlled in Column 2. The estimated coefficient on $HighUCA \times Post$ is 0.209, which implies a statistically and economically significant treatment effect. A one standard deviation increase in $HighUCA \times Post$ was associated with a 9 percent increase in $DLLP$. In Column 3, the fractions of real estate loans, commercial and industrial loans, and personal loans are additionally controlled. In Column 4, lagged LLP is added following Jiang et al. (2016). In both specifications, $HighUCA \times Post$ enters positively and significantly.

In Column 5, we implement propensity score matching to compare the *HighUCA* banks and the control banks with the most similar traits. Each treated bank is matched to a single control bank with replacement based on the characteristics in 2006Q4, a quarter before the assignment of the treatment status. We first require the *HighUCA* banks and the candidate control banks to be in the same *Size, CAP, EBTP*, and *NPL* quintile. Given this condition satisfied, we match each treated bank to a single control bank with the minimum difference in propensity scores with a caliper of 0.05. The propensity scores are estimated using a logit model regressing *HighUCA* on *Size, CAP, EBTP, Ciloans, NPL*, and *Wholesalefunding*.[3] Using the matched sample of banks does not change the results. We find that the *HighUCA* banks increased discretionary provisioning 24 percent more than the control banks with similar traits.

4.3. Dynamic Effects

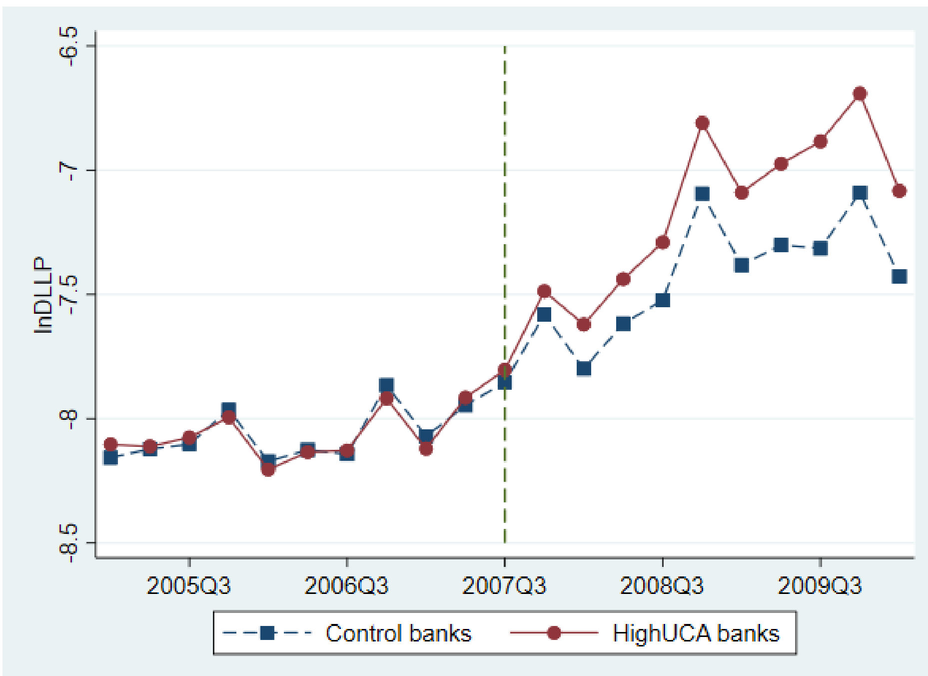
This section addresses the concern that some banks could have predicted the financial crisis. If so, the treatment status might be correlated with unobservable factors that affect bank opacity. First, we visually compare the trends in *lnDLLP* by the *HighUCA* and control

[3] Appendix Table A.2 compares the mean values of the propensity scores and the matching covariates of the *HighUCA* and control banks in the matched sample. The differences in means are statistically insignificant.

banks to see if there were any pre-treatment differences. Figure 4 shows that there was no difference in the level and trend of *lnDLLP* between the *HighUCA* and control banks before the treatment. It was only after the onset of the crisis that the difference became significant.

Figure 4: Discretionary provisioning by the *HighUCA* banks and the control banks

This figure plots the average value of *lnDLLP* (the natural logarithm of discretionary loan loss provisions) in each quarter for the *HighUCA* banks and the control banks. Discretionary loan loss provisions (*DLLP*) are the amount of loan loss provisions, accounted excessively more or excessively less than the necessary amount to cover loan losses. A higher value of *DLLP* indicates higher opacity and lower financial reporting quality. *HighUCA* (control) banks are the banks with *UCA* above (below) the sample median in 2007Q1. The dashed line indicates 2007Q3, the onset of the financial crisis.



Second, we estimate the dynamic version of Model (1) to check the timing of the effect in the regression setting. We replace $HighUCA \times Post$ with multiple interaction terms between *HighUCA* and time period dummy variables. In Table 6, $Before_n$ ($After_n$) equals one for observations from n quarters before (after) the onset of the crisis. $After_0$ is set to one for observations from 2007Q3, the treatment period. $After_{9+}$ equals one for observations from nine or more quarters after the treatment. Table 6, Column 1 includes bank fixed effects and quarter fixed effects, without other control variables. Column 2 includes all the variables controlled in the baseline model in Column 3 of Table 5. Figure 5 presents the results in Column 2 visually by plotting the estimated coefficients and 95% confidence intervals. $HighUCA$ banks and the control banks did not change discretionary provisioning differently before the treatment. The interactions between $HighUCA$ and pre-treatment time dummies enter insignificantly in Column 2. In contrast, the interaction terms of $HighUCA$ and the post-treatment time dummies are positive and mostly significant. The results show that the relatively larger increase in $DLLP$ of the $HighUCA$ banks materialized only after the onset of the crisis, which supports the parallel trend assumption.

Figure 5: Effect of difficulties in liquidity provision on $DLLP$ over time

This figure investigates the dynamic effects of difficulties in liquidity provision on discretionary loan loss provisioning. The figure plots the coefficient estimates on the $HighUCA \times Before_n$ and $HighUCA \times After_n$, reported in Column 2 of Table 6. For $n = 1, 2, ..., 8$, $Before_n$ ($After_n$) equals one if the observation is from n quarters before (after) the onset of the crisis, and zero otherwise. $After_0$ is set to one for observations from 2007Q3, the treatment period. $After_{9+}$ equals one for observations from nine or more quarters after the treatment. $HighUCA$ is a dummy variable that equals one if the bank's UCA was above the sample median in 2007Q1. The vertical lines represent the 95% confidence intervals for the estimates. The dashed line indicates 2007Q3, the treatment period (the onset of the crisis).

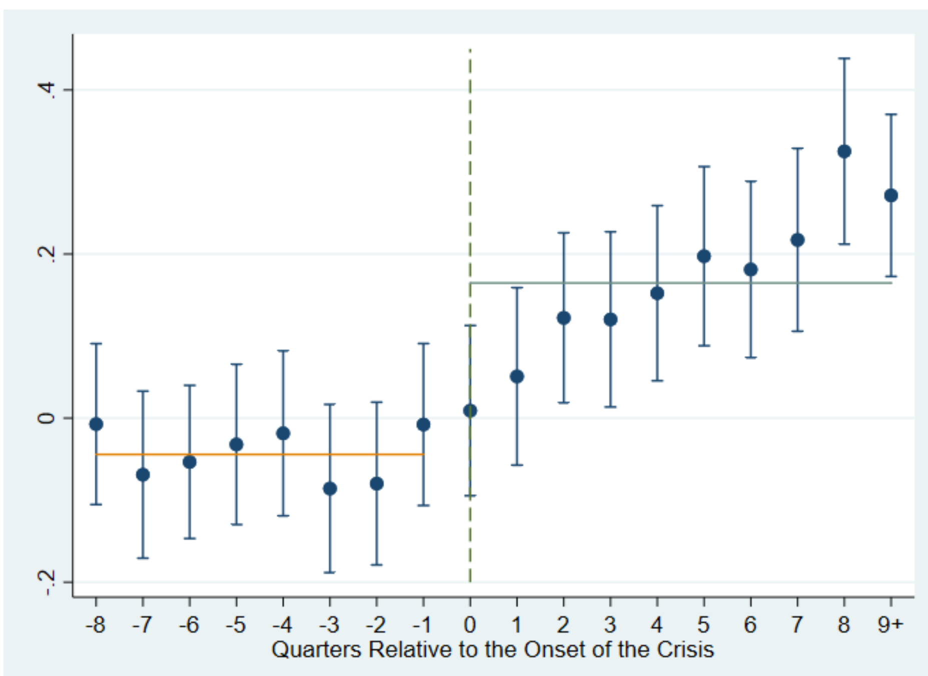


Table 6: Dynamic effects

This table estimates the effect of difficulties in liquidity provision on $DLLP$ over time. The dependent variable is $lnDLLP$, the natural logarithm of discretionary loan loss provisions. For $n = 1, 2, ..., 8$, $Before_n$ ($After_n$) equals one if the observation is from n quarters before (after) the onset of the crisis, and zero otherwise. $After_0$ is a dummy variable set to one for observations from 2007Q3. $After_{9+}$ equals one for observations from nine or more quarters after the treatment. $HighUCA$ is a dummy variable that equals one if the bank's UCA was above the sample median in 2007Q1. Standard errors are clustered at the bank level. The t-statistics are reported in parentheses. ***, **, and * indicate 1%, 5%, and 10% significance, respectively.

	(1)	(2)
VARIABLES	$lnDLLP$	$lnDLLP$
$Before_8 \times HighUCA$	-0.014	-0.007
	(-0.282)	(-0.146)
$Before_7 \times HighUCA$	-0.079	-0.069
	(-1.520)	(-1.328)
$Before_6 \times HighUCA$	-0.065	-0.053
	(-1.357)	(-1.122)
$Before_5 \times HighUCA$	-0.041	-0.032
	(-0.827)	(-0.644)
$Before_4 \times HighUCA$	-0.030	-0.019
	(-0.594)	(-0.362)
$Before_3 \times HighUCA$	-0.101*	-0.086
	(-1.928)	(-1.641)
$Before_2 \times HighUCA$	-0.099*	-0.080
	(-1.951)	(-1.578)
$Before_1 \times HighUCA$	-0.018	-0.008
	(-0.365)	(-0.155)
$After_0 \times HighUCA$	-0.000	0.009
	(-0.001)	(0.172)
$After_1 \times HighUCA$	0.043	0.051
	(0.780)	(0.921)
$After_2 \times HighUCA$	0.133**	0.122**
	(2.520)	(2.313)
$After_3 \times HighUCA$	0.127**	0.120**
	(2.342)	(2.210)
$After_4 \times HighUCA$	0.185***	0.152***
	(3.391)	(2.797)
$After_5 \times HighUCA$	0.224***	0.197***
	(4.013)	(3.544)
$After_6 \times HighUCA$	0.244***	0.181***
	(4.426)	(3.305)
$After_7 \times HighUCA$	0.274***	0.217***
	(4.783)	(3.822)
$After_8 \times HighUCA$	0.390***	0.325***
	(6.720)	(5.633)
$After_{9+} \times HighUCA$	0.337***	0.271***
	(6.533)	(5.386)
Other controls	No	Yes
Bank FE	Yes	Yes
Quarter FE	Yes	Yes
Observations	68,923	68,923
Adjusted R-squared	0.215	0.222

4.4. Robustness Check

4.4.1. Alternative Definitions of *HighUCA* Banks

Table 7: Alternative definitions of the treated banks

This table reports difference-in-differences regression results with alternative definitions of the treated banks. $HighUCA_{tertile}$ ($HighUCA_{quartile}$) is a dummy variable that equals one for banks in the top UCA tertile (quartile) in 2007Q1. $HighUCA_c$ equals the UCA of each bank in 2007Q1. Standard errors are clustered at the bank level. The t-statistics are reported in parentheses. ***, **, and * indicate 1%, 5%, and 10% significance, respectively.

VARIABLES	(1) $lnDLLP$	(2) $lnDLLP$	(3) $lnDLLP$
$HighUCA_{tertile} \times Post$	0.157***		
	(5.668)		
$HighUCA_{quartile} \times Post$		0.172***	
		(5.640)	
$HighUCA_c \times Post$			1.071***
			(6.319)
$Size$	-0.054	-0.049	-0.056
	(-0.987)	(-0.902)	(-1.017)
CAP_{t-1}	-0.023	-0.024	-0.044
	(-0.040)	(-0.041)	(-0.075)
$LOSS_{t-1}$	0.450***	0.451***	0.445***
	(18.952)	(18.982)	(18.731)
$EBTP_{t-1}$	-5.716***	-5.696***	-5.542***
	(-2.762)	(-2.749)	(-2.666)
HHI_{t-1}	-0.423*	-0.434*	-0.438*
	(-1.697)	(-1.748)	(-1.769)
$Reloans_{t-1}$	0.028	0.040	0.040
	(0.097)	(0.139)	(0.137)
$Ciloans_{t-1}$	0.227	0.231	0.251
	(0.681)	(0.690)	(0.751)
$Persloans_{t-1}$	1.010**	1.023**	0.915*
	(2.159)	(2.186)	(1.959)
Bank FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Observations	68,923	68,923	68,923
Adjusted R-squared	0.221	0.221	0.222

In this section, we use different empirical approaches to test the robustness of the results. First, given the positively skewed distribution of banks' *UCA*, we use alternative measures of treatment to see if there is any qualitative change in the results. Treated banks (*HighUCA* banks) are defined as those with a pre-crisis *UCA* higher than the sample median in the main analysis. In Table 7, we change the definition of treated banks using different cutoffs. In Column 1, the treatment status ($HighUCA_{tertile}$) equals one for banks in the top tertile distribution of UCA in 2007Q1, and zero otherwise. In Column 2, $HighUCA_{quartile}$ is defined analogously using the 75th percentile as the cutoff. The results are consistent with those of the main analysis. The difference-in-differences estimates are 0.157 and 0.172 in Columns 1 and 2, respectively. The treated banks increased $DLLP$ more than the control banks after the onset of the crisis. The results align with the hypothesis that banks have an incentive to pursue opacity as liquidity providers.

Lastly, we assume continuous treatment and set $HighUCA_c$ equal to each bank's UCA in 2007Q1. Column 3 reports the results. Banks with a one standard deviation higher UCA before the onset of the crisis increased $DLLP$ about 9 percent more (0.0822×1.071), holding other control variables equal. To summarize, Table 7 shows that the positive treatment effect on discretionary provisioning estimated in the baseline analysis is robust to the alternative definitions of the treated banks.

4.4.2. Alternative Measures of Discretionary Provisioning

Estimating discretionary provisions requires a subjective judgment on the explanatory variables to be included in the LLP model. In Model (2), we include allowances for loan losses (ALW_{t-1}) and net charge-offs (NCO) as explanatory variables for LLP, in addition to the changes in non-performing loans, size, and loan growth. It is based on two assumptions: (1) lagged ALW and NCO are exogenous, and (2) banks should consider the size of existing buffers (ALW) and realized credit losses (NCO) in accounting loan loss provisions. We conjecture that these assumptions are likely to be true, especially during financial distress.

However, in Table 8, we relax these assumptions and test the sensitivity of the results to different measures of discretionary provisioning. Following Beatty and Liao (2014), we estimate $DLLP$ excluding either ALW (Column 1), NCO (Column 2), or both (Column 3)

Table 8: Alternative measures of *DLLP*

This table reports difference-in-differences regression results with alternative measures of *DLLP*. The dependent variables in Columns 1 and 2 are the natural logarithm of *DLLP* estimated using Model (2), excluding *ALW* and *NCO*, respectively. *DLLP* used in Column 3 is estimated with Model (2) excluding both *ALW* and *NCO*. In Columns 4 and 5, the estimation model for *DLLP* is the same as in Model (2), but a longer estimation period is used (2004Q1-2010Q1 for Column 4, and 2003Q1-2010Q1 for Column 5). Column 6 reports the regression result using *DLLP* estimated with Model (4) as the dependent variable. Standard errors are clustered at the bank level. The t-statistics are reported in parentheses. ***, **, and * indicate 1%, 5%, and 10% significance, respectively.

VARIABLES	(1) $lnDLLP$ (excluding ALW)	(2) $lnDLLP$ (excluding NCO)	(3) $lnDLLP$ (excluding both)	(4) $lnDLLP$ (2004Q1-2010Q1)	(5) $lnDLLP$ (2003Q1-2010Q1)	(6) $lnDLLP$ (Model (4))
$HighUCA \times Post$	0.183***	0.141***	0.037*	0.202***	0.203***	0.199***
	(7.062)	(5.706)	(1.661)	(7.801)	(7.916)	(7.617)
$Size$	-0.081	-0.183***	-0.097**	-0.077	-0.095*	-0.138***
	(-1.503)	(-3.662)	(-2.039)	(-1.378)	(-1.763)	(-2.585)
CAP_{t-1}	-0.116	0.489	-0.672	-0.105	-0.018	0.371
	(-0.206)	(0.894)	(-1.405)	(-0.172)	(-0.031)	(0.675)
$LOSS_{t-1}$	0.444***	0.463***	0.373***	0.441***	0.446***	0.439***
	(19.039)	(20.769)	(17.027)	(18.419)	(18.788)	(18.454)
$EBTP_{t-1}$	-5.636***	-5.770***	-7.656***	-5.950***	-6.096***	-2.777
	(-2.800)	(-3.026)	(-4.408)	(-2.717)	(-2.913)	(-1.400)
HHI_{t-1}	-0.355	0.220	-0.066	-0.435*	-0.466*	-0.238
	(-1.447)	(0.803)	(-0.263)	(-1.752)	(-1.905)	(-0.925)
$Reloans_{t-1}$	-0.081	-0.457	-0.445	-0.008	0.022	-0.406
	(-0.276)	(-1.581)	(-1.565)	(-0.028)	(0.077)	(-1.372)
$Ciloans_{t-1}$	0.102	-0.686**	-0.595*	0.201	0.184	-0.194
	(0.303)	(-2.052)	(-1.890)	(0.600)	(0.567)	(-0.563)
$Persloans_{t-1}$	0.760	0.027	0.072	0.833*	0.813*	0.568
	(1.578)	(0.054)	(0.167)	(1.780)	(1.748)	(1.151)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	68,923	68,923	68,923	68,923	68,923	68,923
Adjusted R-squared	0.227	0.247	0.206	0.222	0.225	0.269

from Model (2), and use the estimated $DLLP$ as dependent variables. The results in Table 8 show that the estimated difference-in-differences effects are positive and statistically significant regardless of the specification.

In Table 8, Columns 4 and 5, the dependent variables (natural logarithm of $DLLP$) are estimated using Model (2), but with longer estimation periods. A potential benefit of using longer estimation periods is improvement in the accuracy of the measurement. In Column 4, the estimation period of $DLLP$ is from 2004Q1 to 2010Q1, and in Column 5, from 2003Q1 to 2010Q1. The results are very similar to the baseline results in Column 3 of Table 5. Banks with larger unused commitments before the crisis increased $DLLP$ significantly more than banks with less unused commitments.

Finally, $DLLP$ in Column 6 is estimated using the following model that includes interaction terms of $Post$ and the control variables.

$$
\begin{aligned}
LLP_{i,s,t} = \alpha_0 + \alpha_1 dNPL_{i,s,t+1} + \alpha_2 dNPL_{i,s,t} + \alpha_3 dNPL_{i,s,t-1} + \alpha_4 dNPL_{i,s,t-2} + \alpha_5 Size_{i,s,t-1} \\
+ \alpha_6 LoanGrowth_{i,s,t} + \alpha_7 ALW_{i,s,t-1} + \alpha_8 NCO_{i,s,t} + \alpha_9 GDP_t + \alpha_{10} CSRET_t \\
+ \alpha_{11} dUNEMP_{s,t} + Post \times (\beta_1 dNPL_{i,s,t+1} + \beta_2 dNPL_{i,s,t} + \beta_3 dNPL_{i,s,t-1} \\
+ \beta_4 dNPL_{i,s,t-2} + \beta_5 Size_{i,s,t-1} + \beta_6 LoanGrowth_{i,s,t} + \beta_7 ALW_{i,s,t-1} + \beta_8 NCO_{i,s,t} \\
+ \beta_9 GDP_t + \beta_{10} CSRET_t + \beta_{11} dUNEMP_{s,t}) + \epsilon_{i,s,t} \quad (4)
\end{aligned}
$$

This model incorporates the possibility that banks may be more conservative in loan loss provisioning during the crisis period. For example, banks might set aside more provisions for the same amount of non-performing loans. The estimated coefficient in Column 6 is again very similar to the baseline analysis.

4.4.3. Positive vs. Negative *DLLP*

This section considers positive ($\epsilon > 0$ in Model (2)) and negative ($\epsilon < 0$ in Model (2)) discretionary provisioning separately, following Kanagaretnam et al. (2010), Kim et al. (2019), and Dal Maso et al. (2018). This exercise helps explore the possibility that $HighUCA$ banks increased $DLLP$ to manage reported earnings rather than to increase financial reporting opacity. As negative discretionary provisions result in an increase in net income, $HighUCA$ banks could have accrued less loan loss provisions ($\epsilon < 0$) to window dress earnings or to use the extra money to fund future lending. This earnings management incentive would increase $DLLP$

Table 9: Positive vs. negative *DLLP*

This table estimates the effect of difficulties in liquidity provision on positive and negative discretionary loan loss provisions. The dependent variable in Column 1 is the estimated residuals (ϵ) from Model (2). Column 2 (Column 3) uses $lnDLLP$ as the dependent variable and studies cases where ϵ is positive (negative). Standard errors are clustered at the bank level. The t-statistics are reported in parentheses. ***, **, and * indicate 1%, 5%, and 10% significance, respectively.

VARIABLES	(1) Residuals (ϵ)	(2) $lnDLLP$ ($\epsilon > 0$)	(3) $lnDLLP$ ($\epsilon < 0$)
$HighUCA \times Post$	0.000***	0.351***	0.142***
	(6.964)	(8.351)	(4.817)
$Size$	-0.000*	-0.250***	0.108
	(-1.844)	(-3.102)	(1.576)
CAP_{t-1}	0.003**	1.359*	-1.155
	(2.450)	(1.670)	(-1.637)
$LOSS_{t-1}$	0.000	0.396***	0.467***
	(1.214)	(11.119)	(15.110)
$EBTP_{t-1}$	0.002	-6.138**	-5.208**
	(0.435)	(-1.985)	(-1.970)
HHI_{t-1}	0.001	-0.395	-0.672**
	(1.579)	(-1.053)	(-2.141)
$Reloans_{t-1}$	-0.000	-0.454	0.438
	(-0.271)	(-0.974)	(1.219)
$Ciloans_{t-1}$	0.001	0.240	0.351
	(1.171)	(0.437)	(0.877)
$Persloans_{t-1}$	-0.002***	-0.030	1.907***
	(-3.463)	(-0.037)	(3.566)
Bank FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Observations	68,923	28,472	40,373
Adjusted R-squared	0.015	0.284	0.200

defined as the absolute value of the residuals in Model (2) ($|\epsilon|$). However, it is not relevant to banks' intention to obfuscate loan portfolio quality.

To test this alternative explanation, we first use ϵ from Model (2) as the dependent variable instead of the natural logarithm of $DLLP$ ($|\epsilon|$) in Table 9, Column 1. $HighUCA \times Post$ enters positively, implying that the *HighUCA* banks accrued larger discretionary provisions than control banks after the onset of the crisis, even though it decreased reported earnings. The result is inconsistent with the earnings management explanation. Columns 2 and 3 separate the cases of positive and negative ϵ and estimate Model (1) respectively following

Kanagaretnam et al. (2010), Kim et al. (2019), and Dal Maso et al. (2018). The results show that the relative increase in discretionary provisioning of *HighUCA* banks arose from both larger positive and larger negative residuals rather than from one direction.

These results also help attenuate another concern that credit line loans are commonly held by large firms and thus less risky than term loans. If Model (2) fails to capture this difference in risk profiles,[4] the measure $DLLP$ ($|\epsilon|$) might falsely capture less provisioning for less risky loans as higher discretionary provisioning. However, the results in Table 9 are inconsistent with this alternative explanation that *HighUCA* banks are provisioning less for credit line loans.

4.4.4. Crisis and the Effects of Control Variables

Finally, we allow for the possibility that the effects of the control variables vary before and after the treatment. For example, banks may be more reluctant to report losses after the onset of a crisis, and thus engage more in discretionary provisioning. We interact *Post* with *Size*, *CAP*, *LOSS*, *EBTP*, *HHI*, and the loan portfolio variables, and augment Model (1) with the interaction terms. The estimation results, reported in Table 10, show that banks that reported negative net income last quarter increased $DLLP$ relatively more after the onset of the crisis. The coefficient estimates of $Size \times Post$ are negative, probably due to the intense regulatory scrutiny on large banks during the crisis. Meanwhile, we consistently obtain positive estimates of the treatment effect, which rule out the conjecture that the previous findings were driven by the interaction of the control variables and the crisis period effect.

[4] Model (2) controls for the effect of loan portfolio risk by including changes in non-performing loans in $t-2, t-1, t$, and $t+1$, but this may not be perfect.

4.5. Falsification Test

Another potential concern is that other changes in the banks' environment in the post-treatment period might explain the different discretionary provisioning between the treated and control banks. For example, there may be a match between firms and banks that prefer to borrow and lend with credit lines. If firms with large credit lines behave differently from the other firms during the crisis, then there is a reason to believe that the difference in borrowers' behavior, not the difficulties in liquidity provision, may be the driving force of the results. To alleviate this concern, we perform a placebo test using a sample from the 2001 recession. This approach follows Almeida et al. (2011), who explain that firms did not face significant credit supply shocks in 2001. Figure 1 supports this argument. There was no sudden decrease in unused commitments during the 2001 crisis.

Therefore, if the different behavior of firms with large and small credit lines was the reason why *HighUCA* banks engaged more in discretionary provisioning during the 2007-2009 crisis, the same effect should be observed in the 2001 crisis. On the contrary, if the difficulty in liquidity provision was the true driving force, then the change in *DLLP* should not be different between the treated and control banks around the 2001 crisis.

To investigate the 2001 crisis, we redefine *HighUCA* and *Post* as if there was a shock to the banks' liquidity provision in the 2001 recession. $Post_{2001}$ equals one for 2001Q1 and after. We consider banks with unused commitments to assets ratios higher than the sample median in 2000Q3 as treated banks ($HighUCA_{2001} = 1$). $HighUCA_{tertile,2001}$ ($HighUCA_{quartile,2001}$) equals one for banks in the top tertile (quartile) distribution of *UCA*, and zero for the other banks. $HighUCA_{c,2001}$ is the continuous treatment variable, which equals banks' *UCA* in 2000Q3.

Table 11 reports the falsification test results on the 2001 crisis. Panel A compares liquidity provision of the treated and control banks. Column 1 reports the regression results on *Drawdown*. The estimated effect of pre-crisis commitments on the change of *Drawdown* is positive as 0.002, but much smaller than the effect observed in the 2007 financial crisis (Column 1, Table 4). Column 2 shows that the change in deposit growth of the $HighUCA$ banks was not smaller than that of the control banks, which leads to a 0.002 difference in the change in $NetDrawdown$ reported in Column 3. These results suggest that in the 2001 recession, $HighUCA$ banks did not particularly go through more difficulties in liquidity provision compared to the control banks. Panel B compares discretionary provisioning of the $HighUCA$ banks and the control banks around the 2001 recession. In Column 1, the difference-in-differences coefficient estimate on $HighUCA_{2001} \times Post_{2001}$ is negative and statistically insignificant. Using the alternative treatment variables in Columns 2-4 does not change the result.

4.6. Heterogeneous Effects

The relationship between financial reporting opacity and the difficulties in providing liquidity is likely to vary across banks. First, if there are both informed and uninformed investors (Gorton and Pennacchi, 1990; Dang et al., 2017), and if that is what makes opacity beneficial for banks, the treatment effect should be larger for low-quality than high-quality banks. During distress, both high- and low-quality banks would lose financing from uninformed investors. However, high-quality banks would be able to obtain financing from informed investors, which is not possible for low-quality banks (Pérignon et al., 2018). Therefore, we expect to detect a larger increase in discretionary provisioning for low-quality banks. Table 12, Columns 1 and 2 split the banks into low- and high-quality banks based on profitability ($EBTP_{t-1}$). Banks with lagged $EBTP$ below (above) the 75th percentile are defined as low- (high-) quality banks. The difference-in-differences estimates are positive and significant for both high- and low-quality banks, but the size of the effect for low-quality banks is almost twice as large as that for high-quality banks.

Second, Columns 3 and 4 test whether banks with an older depositor base reacted differently from the other banks. Seniors hold large amounts of money in bank deposits (Becker,

Table 10: Crisis and the effect of control variables

This table estimates the effect of difficulties in liquidity provision on *DLLP*, allowing time shocks to change the effect of control variables. Model (1) is augmented with the interaction terms of *Post* and the control variables (*Size, CAP, LOSS, EBTP, HHI,* and the loan portfolio variables). Some of the coefficient estimates are omitted from the table for brevity. Standard errors are clustered at the bank level. The t-statistics are reported in parentheses. ***, **, and * indicate 1%, 5%, and 10% significance, respectively.

VARIABLES	(1) *lnDLLP*	(2) *lnDLLP*	(3) *lnDLLP*	(4) *lnDLLP*
$HighUCA \times Post$	0.210***			
	(7.526)			
$HighUCA_{tertile} \times Post$		0.169***		
		(5.673)		
$HighUCA_{quartile} \times Post$			0.190***	
			(5.880)	
$HighUCA_{c} \times Post$				1.305***
				(7.017)
$Size$	-0.073	-0.066	-0.062	-0.057
	(-1.373)	(-1.233)	(-1.156)	(-1.056)
$Size \times Post$	-0.044***	-0.038***	-0.038***	-0.055***
	(-3.314)	(-2.780)	(-2.815)	(-3.919)
CAP_{t-1}	-0.226	-0.156	-0.123	-0.216
	(-0.371)	(-0.255)	(-0.200)	(-0.352)
$CAP_{t-1} \times Post$	0.263	0.105	0.040	0.214
	(0.563)	(0.222)	(0.084)	(0.458)
$LOSS_{t-1}$	0.191***	0.198***	0.198***	0.191***
	(3.562)	(3.667)	(3.663)	(3.545)
$LOSS_{t-1} \times Post$	0.273***	0.267***	0.268***	0.273***
	(4.656)	(4.527)	(4.547)	(4.629)
$EBTP_{t-1}$	-6.596**	-6.105**	-6.061*	-6.615**
	(-2.144)	(-1.972)	(-1.955)	(-2.123)
$EBTP_{t-1} \times Post$	4.438	3.733	3.721	4.623
	(1.365)	(1.140)	(1.136)	(1.405)
Other controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Observations	68,923	68,923	68,923	68,923
Adjusted R-squared	0.226	0.226	0.226	0.226

Table 11: Falsification test on 2001 recession

This table reports falsification test results using the sample around the 2001 recession. The sample period is from 1998Q3 to 2003Q3 (from 10 quarters before to 10 quarters after the onset of the recession in 2001Q1). Panel A compares credit drawdowns and deposit inflows to the $HighUCA$ banks and control banks. $HighUCA_{2001}$ equals one if the bank's UCA was higher than the sample median in 2000Q3. $HighUCA_{c,2001}$ equals the UCA of each bank in 2000Q3. $Post_{2001}$ is a dummy variable set to one for the quarters 2001Q1 and after. Three dependent variables are used to measure difficulties in liquidity provision. $Drawdown$ is defined as the decrease in unused commitments (unused commitments in $t-1$ minus unused commitments in t) divided by lagged assets. $\Delta Deposits$ equals the change in deposits divided by lagged assets. $NetDrawdown$ is $Drawdown$ minus $\Delta Deposits$. Panel B compares discretionary loan loss provisions of the $HighUCA$ banks and control banks. The dependent variable is $lnDLLP$, which is the natural logarithm of discretionary loan loss provisions ($DLLP$). In Panels A and B, standard errors are clustered at the bank level. The t-statistics are reported in parentheses. ***, **, and * indicate 1%, 5%, and 10% significance, respectively.

Panel A: Pre-crisis unused commitments and liquidity provision			
	(1)	(2)	(3)
VARIABLES	$Drawdown$	$\Delta Deposits$	$NetDrawdown$
$HighUCA_{2001} \times Post_{2001}$	0.002***	0.000	0.002***
	(7.851)	(0.324)	(2.588)
NPL_{t-1}	0.068***	-0.232***	0.299***
	(5.280)	(-8.923)	(9.863)
CAP_{t-1}	-0.009	0.302***	-0.319***
	(-1.063)	(12.364)	(-11.930)
$Wholesalefunding_{t-1}$	0.008***	0.093***	-0.087***
	(3.170)	(14.653)	(-12.416)
$Size_{t-1}$	0.001*	-0.022***	0.023***
	(1.884)	(-9.645)	(9.163)
$Reloans_{t-1}$	0.009***	-0.005	0.014***
	(4.941)	(-1.181)	(2.966)
Bank FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Observations	55,197	55,197	55,197
Adjusted R-squared	0.007	0.137	0.119

Panel B: The effect on discretionary loan loss provisions				
	(1)	(2)	(3)	(4)
VARIABLES	$lnDLLP$	$lnDLLP$	$lnDLLP$	$lnDLLP$
$HighUCA_{2001} \times Post_{2001}$	-0.026			
	(-1.065)			
$HighUCA_{tertile,2001} \times Post_{2001}$		-0.014		
		(-0.504)		
$HighUCA_{quartile,2001} \times Post_{2001}$			-0.028	
			(-0.948)	
$HighUCA_{c,2001} \times Post_{2001}$				-0.234
				(-1.368)
$Size$	-0.029	-0.033	-0.030	-0.027
	(-0.613)	(-0.700)	(-0.641)	(-0.563)
CAP_{t-1}	-0.751	-0.753	-0.743	-0.745
	(-1.197)	(-1.202)	(-1.186)	(-1.188)
$LOSS_{t-1}$	0.399***	0.399***	0.400***	0.399***
	(9.980)	(9.975)	(9.983)	(9.981)
$EBTP_{t-1}$	8.463***	8.458***	8.432***	8.436***
	(3.919)	(3.914)	(3.902)	(3.899)
HHI_{t-1}	-0.329	-0.337	-0.329	-0.319
	(-0.891)	(-0.912)	(-0.890)	(-0.864)
$Reloans_{t-1}$	0.079	0.079	0.074	0.077
	(0.347)	(0.345)	(0.327)	(0.337)
$Ciloans_{t-1}$	0.539**	0.537**	0.531**	0.526**
	(2.133)	(2.122)	(2.098)	(2.083)
$Persloans_{t-1}$	0.109	0.104	0.103	0.108
	(0.390)	(0.373)	(0.369)	(0.387)
Bank FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Observations	55,197	55,197	55,197	55,197
Adjusted R-squared	0.172	0.172	0.172	0.172

Table 12: Heterogeneous effects

This table compares the effect of difficulties in liquidity provision across subsamples of banks. The dependent variable is $lnDLLP$, which is the natural logarithm of discretionary loan loss provisions ($DLLP$) in all columns. $HighUCA$ is a dummy variable set to one for the banks with UCA higher than the sample median in 2007Q1. $Post$ equals one for the quarters 2007Q3 and after. High (low) profit banks in Column 2 (Column 1) are those with $EBTP_{t-1}$ above (below) the 75th percentile. In Columns 3 and 4, banks are split into two groups based on the fraction of seniors in the banks' local markets. We calculated the fraction of the senior population for each county and the average of the fractions across counties where the banks have branches. Calculating the average, the shares of deposits the banks raise from the counties are used as weights. If the weighted average of the senior fractions is above the 75th percentile in the last quarter (in $t-1$), the bank is in the *More seniors* group. If not, the bank is classified into the *Fewer seniors* group. In Columns 5 and 6, banks are classified as large if $Size_{t-1}$ is in the top quartile of the sample distribution and small otherwise. In Column 8, banks are considered public if either the banks or their parents have a CRSP link in the dataset provided by the New York FRB. Otherwise, banks are classified as private banks (included in the regression in Column 7). Standard errors are clustered at the bank level. The t-statistics are reported in parentheses. ***, **, and * indicate 1%, 5%, and 10% significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Low profit	High profit	Fewer seniors	More seniors	Small	Large	Private	Public
$HighUCA \times Post$	0.213***	0.125**	0.213***	0.149***	0.258***	0.082	0.243***	0.132*
	(7.186)	(2.304)	(7.081)	(2.705)	(8.475)	(1.390)	(8.566)	(1.690)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	51,618	16,765	51,681	16,506	51,674	17,188	57,968	10,937
Adjusted R-squared	0.239	0.191	0.235	0.179	0.217	0.250	0.220	0.242

2007; Becker et al., 2011) and have higher costs of switching banks (Choi and Choi, 2020). If the seniors' deposit supply is less elastic, banks with more senior depositors would find it less beneficial to stay opaque. Columns 3 and 4 empirically test this prediction. We calculated the fraction of seniors (65 or older) out of the total population for each county based on the Population and Housing Unit Estimates data set. Next, for each bank, we calculated the average senior fraction across the counties where the bank has branches. If the average fraction of seniors was lower (higher) than the 75th percentile of the sample, the bank is classified as having fewer (more) senior depositors. The regression results in Columns 3 and 4 in Table 12 show that the effect of increasing *DLLP* is larger for banks with fewer senior depositors. The result implies that branching in areas with a higher number of seniors benefits banks with a large and inelastic deposit supply, and this benefit remained in effect during the crisis period.

Finally, in Columns 5-8, we compare the difference-in-differences estimates of Model (1) for groups of banks categorized by asset size and listing status. This study assumes that banks faced difficulties in raising enough funds to meet the soaring credit drawdowns and new loan demands during the crisis. If this was the case, small banks and private banks would have reacted more sensitively to the difficulties. Large banks and public banks receive financing from better-informed investors, including institutional investors, and thus are able to sustain funding from them. Furthermore, they face intense regulatory scrutiny that requires more transparency. On the other hand, small banks and private banks were likely to lack alternative sources of financing and thus depend more heavily on deposits.

The results in Columns 5-8 align with this hypothesis. In Columns 5 and 6, banks in the top quartile distribution of lagged asset size are classified as large banks and the others as small banks. The difference-in-differences estimate is 0.258 for small banks, which is larger than the benchmark case in Column 3 of Table 5. In contrast, the difference in the changes of *DLLP* between the *HighUCA* banks and the control banks is insignificant for the group of large banks. Columns 7 and 8 compare the private and public banks. The estimated effect is much larger and statistically more significant for private banks.

Table 13: Instrumental variable approach

This table reports 2SLS regression results on the effect of difficulties in liquidity provision. The dependent variable is $lnDLLP$, which is the natural logarithm of discretionary loan loss provisions. The second-stage key independent variable is $NetDrawdown$, which equals the decrease in unused commitments minus the change in deposits scaled by lagged assets. The model in Column 2 uses $HighUCA \times Post$ as the instrumental variable, and Column 1 reports the corresponding first-stage regression results. Column 4 uses $HighUCA_c \times Post$ as the instrument, and Column 3 reports the first-stage regression results. $HighUCA$ is a dummy variable set to one for banks with UCA higher than the sample median in 2007Q1. $HighUCA_c$ equals the UCA of each bank in 2007Q1. $Post$ equals one if the observation is from 2007Q3 and after. Standard errors are clustered at the bank level. The t-statistics are reported in parentheses. ***, **, and * indicate 1%, 5%, and 10% significance, respectively.

	(1)	(2)	(3)	(4)
VARIABLES	$NetDrawdown$	$lnDLLP$	$NetDrawdown$	$lnDLLP$
$HighUCA \times Post$	0.013***			
	(18.177)			
$HighUCA_c \times Post$			0.093***	
			(17.722)	
$NetDrawdown$		15.844***		11.462***
		(7.766)		(6.480)
$Size$	-0.015***	0.174***	-0.015***	0.119**
	(-8.568)	(2.727)	(-8.392)	(2.022)
CAP_{t-1}	-0.362***	5.704***	-0.365***	4.144***
	(-15.856)	(6.042)	(-16.054)	(4.798)
$LOSS_{t-1}$	0.010***	0.292***	0.009***	0.339***
	(12.635)	(8.733)	(12.297)	(11.086)
$EBTP_{t-1}$	0.015	-5.834***	0.033	-5.923***
	(0.227)	(-2.654)	(0.508)	(-2.802)
HHI_{t-1}	0.016*	-0.710***	0.017*	-0.629**
	(1.822)	(-2.758)	(1.874)	(-2.545)
$Reloans_{t-1}$	0.057***	-0.888**	0.058***	-0.629*
	(4.574)	(-2.319)	(4.679)	(-1.819)
$Ciloans_{t-1}$	0.017	-0.034	0.018	0.043
	(1.229)	(-0.083)	(1.311)	(0.115)
$Persloans_{t-1}$	0.094***	-0.559	0.088***	-0.089
	(5.255)	(-0.952)	(4.950)	(-0.166)
Bank FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Observations	68,923	68,923	68,923	68,923
First stage F-stat		330.4		314.1

4.7. Instrumental Variable Approach

Next, we estimate instrumental variable regression models. We instrument $NetDrawdown$, the measure of funding constraints, with the interaction term between pre-crisis UCA and $Post$ to estimate the effect on discretionary provisioning. Table 13 presents the results. Columns

1 and 2 employ $HighUCA \times Post$ as the instrument. The first-stage result reported in Column 1 shows that $HighUCA$ banks faced higher net drawdowns compared to the control banks after the onset of the crisis, consistent with the analysis in Table 4. The first-stage F-statistic shows that the instrument passes the weak instrument test (Column 2). The second-stage result presented in Column 2 confirms that banks with higher funding constraints, associated with pre-crisis unused commitments, increased discretionary provisioning more than control banks. Columns 3 and 4 use $HighUCA_c \times Post$ as the instrument and present similar results. The estimated coefficient in Column 4 suggests that a one standard deviation increase in $NetDrawdown$ led to an approximately 60 percent increase in discretionary provisioning ($e^{.042*11.462} - 1 = 0.62$).

$NetDrawdown$ focuses on a single asset and a single liability of banks in their role of providing liquidity, i.e., loans and deposits. To take into account the liquidity provision of banks more comprehensively, we turn to Berger and Bouwman (2009)'s measures of liquidity creation. Their measures are calculated as weighted sums of all assets and liabilities of banks. The weights are determined by the liquidation costs of each asset and liability type. We use two measures from Berger and Bouwman (2009), $Catfat$ and $Catnonfat$. $Catfat$ takes into account both on- and off-balance-sheet activities, while $Catnonfat$ does not include off-balance-sheet activities.

Table 14 reports the IV regression results using the changes in $Catfat$ and $Catnonfat$ as the liquidity provision measures replacing $NetDrawdown$ in Table 13.[5] The first-stage results in Columns 1 and 3 indicate that $HighUCA$ banks' liquidity provision decreased more after the onset of the crisis. Based on the $Catfat$ measure which takes into account both on- and off-balance-sheet activities, $HighUCA$ bank's liquidity creation was 0.009 lower after the onset of the crisis compared to that of the control banks. This amount corresponds to 0.29 (-0.009/.0308) standard deviation of $dCatfat$. Columns 2 and 4 present the second-stage results. An increase in liquidity creation measures is negatively correlated with discretionary

[5]In Table 14, $dCatfat$ ($dCatnonfat$) equals the change in $Catfat(Catnonfat)$ scaled by lagged gross total assets.

provisions at banks. Assuming that lower amounts of liquidity creation reflect banks' difficulties in providing liquidity, the results align with the hypothesis on the strategic adjustment of provision figures for the sake of liquidity provision.

Table 14: Comprehensive Measures of Liquidity Creation

This table reports 2SLS regression results using more comprehensive measures of liquidity provisions from Berger and Bouwman (2009). The dependent variable, $lnDLLP$, is the natural logarithm of discretionary loan loss provisions. $dCatfat$ ($dCatnonfat$) equals the change in $Catfat$($Catnonfat$) measure from Berger and Bouwman (2009) scaled by lagged gross total assets. Columns 2 and 4 report the second-stage IV regression results using $HighUCA \times Post$ as the instrumental variable, and Columns 1 and 3 report the corresponding first-stage regression results. $HighUCA$ is a dummy variable set to one for banks with UCA higher than the sample median in 2007Q1. $Post$ equals one if the observation is from 2007Q3 and after. Standard errors are clustered at the bank level. The t-statistics are reported in parentheses. ***, **, and * indicate 1%, 5%, and 10% significance, respectively.

	(1)	(2)	(3)	(4)
VARIABLES	$dCatfat$	$lnDLLP$	$dCatnonfat$	$lnDLLP$
$HighUCA \times Post$	-0.009***		-0.005***	
	(-15.485)		(-12.364)	
$dCatfat$		-23.008***		
		(-7.601)		
$dCatnonfat$				-38.835***
				(-7.231)
Other controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Observations	68,801	68,801	68,801	68,801
First stage F-stat		239.8		152.9

4.8. Earnings Persistence and Cash Flow Predictability

Finally, we study the relationship between liquidity provision difficulties and two other commonly used measures of financial reporting quality: earnings persistence and cash flow predictability of reported earnings. This exercise is not only a good robustness check but also helpful in understanding the channel of the effect. One might argue that $HighUCA$ banks accrue loan loss provisions in a more discretionary manner after the onset of the crisis to smooth earnings, not because opacity helps them to provide liquid securities during distress. In such a case, the relative earnings persistence of $HighUCA$ banks would increase. On the other hand, a relative decrease in earnings quality of $HighUCA$ banks, measured with earnings persistence and cash flow predictability, would be more consistent with the explanation that banks increase financial reporting opacity for the efficient provision of liquidity.

Following Kanagaretnam et al. (2014) and Altamuro and Beatty (2010), we estimate the following models.

$$ROA_{i,t+1} = \beta_1 ROA_{i,t} + \beta_2 HighUCA_i \times Post_t + \beta_3 ROA_{i,t} \times HighUCA_i + \beta_4 ROA_{i,t} \times Post_t + \beta_5 ROA_{i,t} \times HighUCA_i \times Post_t + \gamma X_{i,t-1} + \alpha_i + \delta_t + u_{i,t} \quad (5)$$

$$CF_{i,t+1} = \beta_1 ROA_{i,t} + \beta_2 HighUCA_i \times Post_t + \beta_3 ROA_{i,t} \times HighUCA_i + \beta_4 ROA_{i,t} \times Post_t + \beta_5 ROA_{i,t} \times HighUCA_i \times Post_t + \gamma X_{i,t-1} + \alpha_i + \delta_t + u_{i,t} \quad (6)$$

i and t indicate bank and year, respectively. Considering that annual earnings are important earnings benchmarks for investors and managers (Graham et al., 2005), bank-year level observations are used to estimate these models following the previous studies (Kanagaretnam et al., 2014; Altamuro and Beatty, 2010). Model (5) examines whether $HighUCA$ banks' earnings persistence decreases relatively more than that of the control banks after the onset of the crisis. Earnings persistence refers to the association between current ($ROA_{i,t}$) and future ($ROA_{i,t+1}$) earnings, captured by the coefficient on $ROA_{i,t}$ in Model (5). Model (6) replaces the future earnings ($ROA_{i,t+1}$) in Model (5) with the one-year forward value of cash flows ($CF_{i,t+1}$) to estimate the ability of current earnings to predict the subsequent year's cash flows.[6] In both models, β_5 is the coefficient of the interest. A negative estimate of β_5 implies a decrease in the earnings quality of $HighUCA$ banks compared to that of the control banks after the onset of the crisis.

The estimation results are reported in Table 15. Columns 1-3 study earnings persistence.

[6] ROA equals pre-tax earnings divided by lagged assets. CF equals earnings before taxes and loan loss provisions divided by lagged assets. The summary statistics of variables used in these analyses are reported in Appendix Table A.3.

Regardless of the cutoffs used to define the treated banks, $HighUCA$ banks' earnings persistence decreased more than that of the control banks after the onset of the crisis. The coefficient on $ROA \times Post$ is negative, consistent with the notion that earnings are less persistent during the crisis period. More importantly, the estimated coefficient on the triple interaction term $ROA \times HighUCA \times Post$ is negative and statistically significant at the 1% level. The estimated size of the coefficient is large (-0.157 in Column 1), corresponding to 30% of the size of the coefficient on ROA. Columns 4-6 employ $CF_{i,t+1}$ as the dependent variable. The results indicate that the cash flow predictability of earnings also declines more for the $HighUCA$ banks. Taken together, the results in Table 15 corroborate the earlier findings on the relationship between liquidity provision difficulties and the financial reporting quality of banks and suggest that the increase in $HighUCA$ banks' discretionary provisioning is not just a mere reflection of income smoothing.

5. Conclusion

This study investigates the 2007-2009 financial crisis to examine the relationship between banks' role as liquidity providers and financial reporting opacity. Specifically, we compare banks with high and low pre-crisis unused commitments (*UCA*) with respect to their DLLPs before and after the onset of the crisis. This approach intends to find and exploit an unexpected variation in the difficulties of funding deposits to meet borrowers' credit needs. After the onset of the crisis, large amounts of funds were drawn from the existing lines of credit, which was unlikely to be predicted by banks. The larger the pre-crisis commitments were, the harder it was for banks to honor the commitments in distress.

We find that the financial reporting quality of the *HighUCA* banks decreased more than that of the control banks after the onset of the crisis. Discretionary provisions by the *HighUCA* banks increased about 20 percent more. The effect was especially large for low-quality banks and banks without alternative sources of capital. We also provide the results attenuating

Table 15: Earnings persistence and cash flow predictability

This table estimates the relationship between difficulties in providing liquidity and earnings quality. The dependent variable in Columns 1 and 2 is ROA_{t+1}, which equals the next year's pre-tax earnings divided by current assets. In Columns 3 and 4, CF_{t+1} is used as the dependent variable. CF_{t+1} equals the next year's earnings before taxes and loan loss provisions divided by the current year's assets. *HighUCA* is a dummy variable set to one for the banks with *UCA* higher than the sample median in 2007Q1. $HighUCA_{quartile}$ is a dummy variable that equals one for banks in the top *UCA* quartile in 2007Q1. *Post* equals one for the quarters 2007Q3 and after. Standard errors are clustered at the bank level. The t-statistics are reported in parentheses. ***, **, and * indicate 1%, 5%, and 10% significance, respectively.

VARIABLES	(1) ROA_{t+1}	(2) ROA_{t+1}	(3) CF_{t+1}	(4) CF_{t+1}
ROA	0.520***	0.540***	0.360***	0.363***
	(12.018)	(15.442)	(12.566)	(15.924)
$HighUCA \times Post$	-0.002**		-0.000	
	(-2.167)		(-0.584)	
$ROA \times HighUCA$	0.153**		0.070*	
	(2.395)		(1.734)	
$ROA \times Post$	-0.174***	-0.163***	-0.136***	-0.125***
	(-4.588)	(-5.145)	(-5.403)	(-6.214)
$ROA \times HighUCA \times Post$	-0.157***		-0.079**	
	(-2.609)		(-2.093)	
$HighUCA_{quartile} \times Post$		-0.001		0.001
		(-0.911)		(0.754)
$ROA \times HighUCA_{quartile}$		0.228***		0.126***
		(2.991)		(2.671)
$ROA \times HighUCA_{quartile} \times Post$		-0.314***		-0.176***
		(-4.191)		(-3.849)
$Size_{t-1}$	-0.009***	-0.010***	-0.004***	-0.005***
	(-9.752)	(-10.611)	(-7.057)	(-7.515)
DEP_{t-1}	0.013***	0.013***	0.003	0.003
	(3.551)	(3.502)	(1.186)	(1.135)
$Ciloans_{t-1}$	-0.002	-0.002	0.002	0.002
	(-0.349)	(-0.300)	(0.468)	(0.482)
$Reloans_{t-1}$	-0.011*	-0.011*	-0.005	-0.005
	(-1.783)	(-1.866)	(-1.152)	(-1.187)
$Persloans_{t-1}$	-0.015*	-0.015**	-0.002	-0.002
	(-1.945)	(-1.975)	(-0.302)	(-0.311)
$Public$	-0.003	-0.002	-0.001	-0.001
	(-1.532)	(-1.367)	(-0.519)	(-0.435)
Other controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	17,264	17,264	17,264	17,264
Adjusted R-squared	0.538	0.540	0.575	0.576

concerns that banks adjusted the unused commitments in advance predicting the crisis, and that the results were driven by differences in borrower behavior during the crisis.

The paper calls attention to the positive effects of banks staying opaque. The need to enhance information disclosure has often been discussed. Transparency helps investors and regulators monitor banks more effectively. However, it is important to consider that banks may strategically choose to be opaque to provide liquidity efficiently in times of distress. The direction and magnitude of the effect might be different depending on the contents and channels of disclosure (e.g., financial reports, earnings guidance, and the Management Discussion and Analysis section of 10-K filings), which can provide fruitful topics for future research.

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Appendix

Table A.1: Variable List

Variable	Definitions
LLP	Loan loss provisions divided by lagged loans.
dNPL	Change in non-performing loans divided by lagged loans.
Size	Natural logarithm of assets.
LoanGrowth	Growth rate of loans.
ALW	Loan loss allowance divided by loans.
NCO	Loan charge off minus loan recoveries, divided by lagged loans.
GDP	Growth rate of GDP per capita.
CSRET	Return on the Case-Shiller Real Estate Index.
dUNEMP	Change in the unemployment rate of the state of the bank's location.
lnDLLP	Natural logarithm of discretionary loan loss provisions. Discretionary loan loss provisions are the absolute values of estimated residuals from model (2).
Unused commitments	Unused commitments include the unused amount of loan commitments, letters of credit, securities underwriting, and other commitments (RCFD3814 + RCFD3816 + RCFD3817 + RCFD3818 + RCFD6550 + RCFD3411).
UCA	Unused commitments divided by assets.
CAP	Equity divided by assets.
LOSS	An indicator variable that equals one if the net income is negative, and zero otherwise.
EBTP	Earnings before taxes and provisions divided by lagged loans.
Reloans	Loans secured by real estate divided by loans.
Ciloans	Commercial and industrial loans divided by loans.
Persloans	Loans to individuals divided by loans.
HHI	Average Herfindahl–Hirschman Indices of the bank's deposit markets (counties in which the bank has branches). The fractions of deposits the bank raises from the counties are used as weights to calculate the average.
Drawdown	Decrease in unused commitments (unused commitments in t-1 minus unused commitments in t), divided by lagged assets.
$\Delta Deposits$	Change in deposits divided by lagged assets.
NetDrawdown	*Drawdown* minus $\Delta Deposits$.
$\Delta Credit$	Change in the sum of loans and unused commitments, divided by lagged assets.
NPL	Non-performing loans divided by lagged loans.
Wholesalefunding	Wholesale funds divided by assets. Wholesale funds include large time deposits, foreign deposits, subordinated debt and debentures, federal funds purchased, repos, and other borrowed money.

Table A.2: Matching results

This table compares the mean values of the propensity scores and the matching covariates of *HighUCA* and control banks in the matched sample. Candidate control banks are required to be in the same *Size, CAP, EBTP*, and *NPL* quintile. With this condition satisfied, I match each treated bank to a single control bank with the minimum difference in propensity scores with a caliper of 0.05. The propensity scores are estimated using a logit model regressing *HighUCA* on *Size, CAP, EBTP, Ciloans, NPL*, and *Wholesalefunding*. All matching covariate values are from 2006Q4, a quarter before the assignment of the treatment status. The differences in means reported in the last column are not statistically significant at the 10 percent level.

	$HighUCA$ banks	Control banks	Diff.
Obs.	729	729	
$pscore$	0.490	0.488	0.002
$Size$	12.618	12.627	-0.009
CAP	0.096	0.096	0.000
$EBTP$	0.006	0.006	0.000
$Ciloans$	0.141	0.136	0.006
NPL	0.007	0.007	0.000
$Wholesalefunding$	0.245	0.242	0.004

Table A.3: Summary statistics of the variables used in the earnings quality tests

This table displays summary statistics of the sample used in the tests on earnings persistence and cash flow predictability. Bank-year level observations from 2005 to 2009 are used for the analyses. All continuous variables are winsorized at the 1st and 99th percentiles.

Variable	Obs	Mean	Std. Dev.	P25	P50	P75
ROA_{t+1}	17264	.009	.016	.005	.012	.017
CF_{t+1}	17264	.015	.01	.011	.016	.02
$Size_{t-1}$	17264	12.61	1.04	11.897	12.348	13.022
DEP_{t-1}	17264	.813	.084	.778	.831	.871
$Ciloans_{t-1}$	17264	.155	.096	.088	.137	.201
$Reloans_{t-1}$	17264	.714	.159	.632	.742	.827
$Persloans_{t-1}$	17264	.069	.071	.021	.047	.09
$Public$	17264	.155	.362	0	0	0