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The cost of being safer in banking: Market power loss

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ABSTRACT

To promote safety at financial institutions, Basel III introduced two new liquidity rules, the net stable funding ratio and the liquidity coverage ratio. However, the issue of how the new rules affect the market power of banks has not been investigated. This paper fills the gap by analyzing how an increase in bank liquidity associates with market power for a sample of 2,665 unique commercial banks and bank holding companies in the U.S. during 2000–2015. We find a significantly negative correlation between liquidity and market power. The result is robust over different measures of liquidity and market power and different estimation methods. Our further investigation reveals that banks can expand their business aggressively to enjoy economies of scale to mitigate the negative effect of liquidity on market power.

1. Introduction

The financial crisis of 2007–08 provided an important lesson of how liquidity shortage can bring about the systemic failure of financial institutions (Acharya and Mora, 2015; Khan et al., 2017). To prevent a similar future crisis, the Basel III Accord (Basel Committee on Banking Supervision, 2010) updates the first two accords, introduced in 1988 and 2004, by adopting two required minimum liquidity standards: the net stable funding ratio (NSFR hereafter) and the liquidity coverage ratio (LCR hereafter).

The introduction of the new liquidity standards raises concerns over bank market power, a measure of bank competition (Berger et al., 2009; Spierdijka and Zaourasa, 2018). Some degree of market power is necessary for banks to achieve a mutually efficient bank–firm relationship (Delis et al., 2017). And low market power can also increase the likelihood of bank failure and financial instability (Keeley, 1990). In response to Basel III, financial institutions may rely on long-term funding and hold more liquid assets to improve the liquidity ratios. A greater reliance on long-term funding can incur higher costs than short-term funding, while holding more liquid assets can result in lower revenue than illiquid assets. Therefore, the adoption of the liquidity standards by a bank may potentially increase its costs and reduce its revenue, thus reducing bank market power (Vives, 2011).

Previous studies find that the variability of bank market power comes from several factors such as ownership (Efthyvoulou and Yildirim, 2014), cross-border lending and foreign direct investment bank (Bremus, 2015), consolidation (Angelini and Cetorelli, 2003), size (Maudos and de Guevara, 2007), technical efficiency (Delis and Tsionas, 2009), capital requirements (Agoraki et al., 2011), and diversification (Barbosa et al., 2015). Other studies examine the effect of market power on different forms of risk, such as bank failures (Akins et al., 2016; Martinez-Miera and Repullo, 2010), bank distress (Buch et al., 2013;

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Kick and Prieto, 2015; Koetter and Poghosyan, 2009), systemic risk (Anginer et al., 2014), Z-score (Leroy and Lucotte, 2017; Tabak et al., 2012), and stock return volatility (Forssbæck and Shehzad, 2015). Yet, researchers have not examined empirically the relationship in a reverse way, that is, bank liquidity's effect on market power. Thus our paper empirically investigates how an individual bank's market power changes in response to its improving liquidity.

This paper uses the Lerner index (Lerner, 1934) and the price–cost markup to proxy for bank-year market power. Whereas the Lerner index is computed as the relative difference of output price over marginal cost, the markup is measured as the relative difference of output price over average cost. To capture bank liquidity, we use two liquidity ratios: the NSFR in the baseline regression and the LCR in our robustness check for a sample of 2,665 unique U.S. commercial banks (CBs hereafter) and bank holding companies (BHCs hereafter) over the period 2000–2015.

Our paper has two important findings. First, we find a trade-off between liquidity and market power. Our result is in line with the market power-fragility mechanism in which banks with higher degrees of pricing power can generate more rents by setting higher interest rates for lending. Higher lending interest rates induce borrowers to invest in riskier projects which have higher returns than the lending rates. There is an increased risk level in loan portfolios when banks grant credit to risky projects due to adverse selection and the moral hazard problem (Boyd and De Nicolo, 2005; Stiglitz and Weiss, 1981). In addition, the trade-off may originate from lower revenue and/or higher marginal cost. Regarding revenue, banks with greater liquidity may hold more short-term assets such as cash, deposits at other banks and government bonds. These short-term assets are safer and more liquid but they have lower yields than long-term assets such as loans or investments. Regarding marginal cost, banks with greater liquidity may have to pay more to achieve stability of funding which comes from deposits and long-term bonds. The combination of lower revenue and higher marginal cost will result in a lower level of bank market power. Second, a bank can expand its business aggressively to diminish the negative influence of the bank's liquidity on its market power. This finding is supported by the analysis of Demirgüç-Kunt and Huizinga (2010) who discover that fast growing banks are more profitable (i.e. higher revenue and lower costs).

The results of this paper are important for several reasons. First, our paper contributes to the emerging literature of the impacts of Basel III's liquidity standards on bank performance as well as how banks response to an increase in liquidity requirements. Second, our research explains how a bank's liquidity affects its market power. This explanation, based on new empirical evidence, brings greater clarity to the mixed findings in previous research examining how regulations influence individual bank market power. For example, while the stricter capital standards would allow existing banks to accumulate market power (Agoraki et al., 2011), they may also reduce bank market power (Angelini and Cetorelli, 2003; VanHoose, 2007).

Our paper starts with an introductory section. Section 2 presents a literature review. The variables and data description are presented in Section 3 and Section 4 discusses the estimation results. Section 5 summarizes the findings.

2. Literature review

2.1. Literature relating to the NSFR and the LCR

Prior studies mainly examine how the NSFR and the LCR affect bank efficiency and risk taking. Regarding bank risk taking, liquidity shortage has been seen as an idiosyncratic and systemic threat to financial stability. Khan et al. (2017) reveal that a liquidity reduction augments bank risk (proxied by liquidity creation, risk-weighted assets, and Z-scores). On the other hand, greater liquidity could help banks reduce the risk of failure through systematic and idiosyncratic channels (Hong et al., 2014). Regarding bank efficiency, there are inconsistent conclusions on the relationship between liquidity and profitability. King (2013) finds a trade-off between liquidity and profitability for 549 banks in 15 countries. However, Dietrich et al. (2014) provide evidence that liquidity (proxied by the NSFR) has no influence on profitability (proxied by return on assets (ROA), return on equity (ROE), and net interest margin) for Western European banks during the period 1996–2010.

2.2. Bank regulatory and market power

The literature highlights three types of bank regulation: ''capital requirements, official supervisory power, and restrictions on bank activities'' (Fiordelisi et al., 2015). Capital requirement shows mixed effects on bank market power. On the one hand, capital requirements can influence market power because higher initial capital requirements require banks to be larger and therefore create entry barriers for both new and current players. Similarly, high capital requirements can result in higher fixed costs, which are consequently more affordable for many banks and in particular existing banks. Thus, stricter capital standards would allow existing banks to accumulate market power (Agoraki et al., 2011). On the other hand, higher capital standards may adversely influence bank market power by increasing the cost of raising capital, reducing total loans and reducing revenues from bank assets (VanHoose, 2007). The analyses of Angelini and Cetorelli (2003) show that regulatory reform in Italy (the Second Banking Directive in 1993) reduced bank markups during the 1990s.

The official supervisory process can have very different impacts on bank market power and in some cases can prevent banks from accumulating market power (Levine, 2003). However, big banks can enhance their market power by using their influence with politicians and inducing supervisors to serve the interest of the banks rather borrowers (Stigler, 1971; Agoraki et al., 2011). In addition, a bank's physical constitution and performance have changed due to the application of more severe regulations embodied in the Basel Accord III (Wu et al., 2018).

Previous empirical studies show that restrictions on bank activities have a mixed impact on market power. Laeven and Claessens (2004) in a survey of 50 countries studied whether regulations and market structures drive bank competitiveness. They found that a lower level of restrictions on activity results in diminished market power in the countries where there exist fewer activity restrictions and a greater foreign bank presence. However, Beck et al. (2004) reach an opposite conclusion: that is, banks in an environment of lower restrictions can gain market power via merging to form large financial conglomerates.

2.3. Other determinants of market power

Studies which examine the impacts of market structure and contestability on bank market power have had quite different conclusions. Mirzaei and Moore (2014) investigate the drivers of bank market power in 146 countries during 1999–2011 and find a mixed relationship between bank-concentration and market power. They find it is positive in developing countries, negative in advanced countries, and not significant in emerging countries. Contestability and institutional development have negative impacts on market power in developing countries. Financial freedom and inter-industry competition seem to reduce market power in advanced countries. In emerging countries, foreign bank penetration reduces market power due to a spillover effect (Jeon et al., 2011). However, Delis (2012) finds no link between market concentration and market power.

The literature also highlights diversification as a driver of market power. Barbosa et al. (2015) investigate how multi-product banking operations influence bank market power for Brazilian banks from 2001 to 2012. The authors find that greater diversification can result in substantially greater market power. In the same vein, Vennet (2002) shows that multi-product banks can derive greater market power given they are able to increase revenue ("more revenue efficient") and reduce costs (cost efficiency due to scope economies). From a study of 19,322 bank-year observations in Europe over the period 1994 to 2000, Valverde and Fernández (2007) show that diversification permits banks to attain greater market power through increasing their revenue from non-lending activities.

Other studies find that the variability of bank market power also comes from various factors such as cross-border lending, foreign ownership, and efficiency in the banking sector. Bremus (2015) employs "a two-country general equilibrium model with heterogeneous banks" to explain why foreign direct investment and cross-border lending mitigate market power and thus reduce market power. Similarly, foreign-owned banks tend to have greater market power compared to privately-owned domestic banks in Central and Eastern European countries during 2002–2010 (Efthyvoulou and Yildirim, 2014). Efficiency has a mixed effect on market power. On the one hand, efficiency and market power were negatively associated with each other for commercial banks in Western European countries during 1999–2006 (Delis and Tsionas, 2009). On the other hand, cost efficiency has a positive relationship with market power in the EU-15 countries for the period 1993–2002 (Maudos and de Guevara, 2007).

3. Variables and data description

3.1. Market power proxies

We use the Lerner index as the main proxy for market power because of its useful analytical implications (Anginer et al., 2014; Beck et al., 2013). First, the index accounts for a bank's pricing power of its product through which its franchise value is created. Second, because the index is computed as the difference between operating income and financial and operational costs, the index better captures the concept of the intermediation function in dealing with both asset and funding management. To guarantee linear homogeneity of degree one in input prices, we normalize input prices and total costs with price of deposits ($W_{1,it}$). To compute marginal cost, we follow Spierdijka and Zaourasa (2018) to estimate the translog cost function below:

$$\begin{aligned}\log\left(\widetilde{TC}_{it}\right) &= \alpha + b_0 \times \log\left(Q_{it}\right) + b_1 \times \frac{1}{2} \times \left(\log\left(Q_{it}\right)\right)^2 + a_2 \times \log\left(\tilde{W}_{2,it}\right) \\ &+ a_3 \times \log\left(\tilde{W}_{3,it}\right) + b_3 \times \log\left(Q_{it}\right) \times \log\left(\tilde{W}_{2,it}\right) + b_4 \times \log\left(Q_{it}\right) \times \log\left(\tilde{W}_{3,it}\right) \\ &+ a_6 \times \log\left(\tilde{W}_{2,it}\right) \times \log\left(\tilde{W}_{3,it}\right) + a_8 \times \frac{1}{2} \times \left(\log\left(\tilde{W}_{2,it}\right)\right)^2 + a_9 \times \frac{1}{2} \times \left(\log\left(\tilde{W}_{3,it}\right)\right)^2 \\ &+ d_1 \times Trend + d_2 \times Trend^2 + d_3 \times Trend \times \log\left(Q_{it}\right) + d_4 \times Trend^2 \times \log\left(Q_{it}\right) + \varepsilon_{it} \end{aligned} \quad (1)$$

where $\log\left(\widetilde{TC}_{it}\right)$ is the natural logarithm of the normalized total costs scaled by $W_{1,it}$. Q_{it} is total output and is proxied by total assets. $W_{1,it}$ is funding costs (proxied by the proportion of total interest expenses over total assets). $\tilde{W}_{2,it}$ denotes labor costs (measured by the normalized ratio of personnel expenses divided by total assets). $\tilde{W}_{3,it}$ is other operating costs (proxied by the normalized share of administrative and other operating expenses in total assets). *Trend* stands for time trend which accounts for changes in technology. The $Trend^2$ term is also included to account for technological changes. With this specification, average cost (AC) and marginal cost (MC) are nonlinear functions of time trend. And ε_{it} is a zero-mean error term. Each bank and year are expressed by subscripts *i* and *t* respectively. We estimate the regression using stochastic frontier analysis (SFA) and the estimation results are presented in Appendix A. Then we use the coefficients estimated from Eq. (1) to capture the marginal cost for an individual bank which can be denoted as:

$$MC_{it} = {}^{\partial TC_{it}}/_{\partial Q_{it}}$$

$$= {}^{TC_{it}}/{}_{Q_{it}} \times \left[\begin{array}{c} b_0 + b_1 \times \log\left(Q_{it}\right) + b_3 \times \log\left(\tilde{W}_{2,it}\right) + b_4 \times \log\left(\tilde{W}_{3,it}\right) \\ +d_3 \times Trend + d_4 \times Trend^2 \end{array} \right] \tag{2}$$

Relying on the computed marginal cost, we estimate the Lerner index as:

$$Lerner_{it} = \frac{P_{it} - MC_{it}}{P_{it}} \tag{3}$$

where P_{it} denotes the asset price and is calculated as the ratio of total operating income[1] to total assets.

In addition to the Lerner index, we follow Bolt and Humphrey (2015) to compute the price–cost markup to capture the bank market power. The markup is determined from:

$$Markup_{it} = \frac{P_{it} - AC_{it}}{P_{it}} \tag{4}$$

where P_{it} is the price of assets as in Eq. (3) and AC_{it} is the average total cost (computed by the proportion of total costs to total assets).

3.2. Liquidity indicators

The Basel Committee on Banking Supervision (2010, 2014) proposed the LCR[2] and the NSFR to reduce the shortage of liquidity. The computation of the NSFR is presented in Eq. (5). It is noted that banks should maintain their LCR and NSFR at a level of no less than 1 to avoid possible liquidity shortages in short-term and long-term stress scenarios. Under the Basel III, the NSFR is a ratio between available stable funding and required stable funding:

$$NSFR = \frac{Available\ stable\ funding\ (ASF)}{Required\ stable\ funding\ (RSF)} = \frac{\sum_i w_i L_i}{\sum_j w_j A_j} \tag{5}$$

where the weights w_i and w_j are bounded between zero and one, L_i is bank liability, and A_j is a bank's assets. ASF and RSF are the weighted sum of liabilities and assets, respectively. To calculate the ASF and RSF, specific weights are applied to funding sources and assets. The weights corresponding to funding sources are called ASF factors and which represent the stability of the funding sources. The more stable the funding, the higher the ASF factor. The weights corresponding to assets are called RSF factors. Unlike the ASF factor, a higher RSF factor represents an asset's lower liquidity level.

The bank dataset in this study is mainly from *Bankscope* and does not provide sufficient information required to compute the NSFR. To approximate the NSFR ratio we therefore follow Vazquez and Federico (2015) in building up a stylized balance sheet and weights (see Table 1, page 4 of Vazquez and Federico (2015)).

The estimation of the LCR requires detailed non-public information about liquid asset levels and 30-day liabilities and is not feasible with the data from *Bankscope*. We then follow Lapteacru (2017), Zhu and Yang (2016) and Chiaramonte and Casu (2017) in using the fraction of liquid assets to deposit and short-term debt to proxy for the LCR for a robustness test of our baseline results. The ratio captures the nature of a bank's liquidity position in the sense that the bank can convert its liquid assets easily and quickly into cash and cash equivalent to meet obligations from its depositors and short-term creditors. Previous studies of Gorton and Huang (2004) and Altunbas et al. (2007) similarly use the fraction of liquid assets to deposits as a liquidity indicator for banks.

3.3. Model specification

We employ the OLS as well as the dynamic panel GMM estimations. Regarding the OLS estimation, we use fixed effects (over bank and time) and cluster by banks as in De Jonghe et al. (2015) to investigate the relationship between liquidity and bank market power as in Eq. (6):

$$Market\ power_{i,t} = \beta_1 \times Liquidity_{i,t} + X_{i,t}\beta + \alpha_i + \lambda_t + \varepsilon_{i,t}. \tag{6}$$

Our dependent variable is individual bank market power (proxied by the Lerner index or the mark-up) of bank *i* in year *t*. Our main explanatory variable is bank liquidity, which is the NSFR in the baseline regression and the LCR in the robustness check. Our control variables, $X_{i,t}$, include diversification, equity capital ratio, assets growth, bank size, the nonperforming loan ratio and a crisis dummy.

Following Curi et al. (2015) and Elsas et al. (2010), we compute three diversification variables, including asset diversification (*ADIV*), funding diversification (*FDIV*) and income diversification (*IDIV*). Specifically, in the computation of *ADIV*, the loans and advances to banks (*IBLOAN*), customer loans (*CLOAN*) financial securities (*FSEC*) and other investments in property (*IP*) are used according to the following equation:

$$ADIV = 1 - \left(\left(\frac{IBLOAN}{EA}\right)^2 + \left(\frac{CLOAN}{EA}\right)^2 + \left(\frac{FSEC}{EA}\right)^2 + \left(\frac{IP}{EA}\right)^2 \right), \tag{7}$$

[1] The sum of interest and non-interest income.

[2] The LCR is computed as the proportion of "high-quality liquid assets" to total projected net cash outflow for the next 30 days.

Table 1
Definition of variables.

Variable	Description	Type
Dependent variables		
LERNER	The Lerner index. The computation of the index is shown in Eqs. (1)–(4).	Bank market power
Markup	A variant of the Lerner index.	Bank market power
Independent variables		
NSFR	Net stable funding ratio.	Liquidity
LCR	Liquidity coverage ratio (proxied by the ratio of a bank's liquid assets to deposit and short-term debt).	Liquidity
ADIV	Asset diversification. The computation of ADIV is presented in Eq. (7).	Firm characteristics
FDIV	Funding diversification. The computation of FDIV is presented in Eq. (8).	Firm characteristics
IDIV	Income diversification. The computation of IDIV is presented in Eq. (9).	Firm characteristics
TIER1	Tier 1 regulatory capital ratio.	Firm characteristics
ASSETGR	Annual growth of total assets.	Firm characteristics
SIZE	The logarithm of total assets.	Firm characteristics
NPL	Period non-performing loans over total loans.	Performance
CRISIS	A dummy variable for financial crisis years 2007 and 2008.	Market/environment

This table presents the definitions of variables. We calculate the Lerner index (L), the markup, three diversification indicators (*ADIV, FDIV, and IDIV*) and the NSFR. Other variables, including *LCR, TIER 1, ASSETGR, SIZE* and *NPL* are collected from *Bankscope*.

where EA is the total earning assets which is equal to the sum of the four numerators.

In the calculation of funding diversification ($FDIV$), equity ($EQUI$), deposits from non-bank customers ($CDEP$), deposits from bank customers ($IBDEP$) and other liabilities ($ODEBT$) are used as below:

$$FDIV = 1 - \left(\left(\frac{EQUI}{FUND} \right)^2 + \left(\frac{CDEP}{FUND} \right)^2 + \left(\frac{IBDEP}{FUND} \right)^2 + \left(\frac{ODEBT}{FUND} \right)^2 \right) \tag{8}$$

where $FUND$ is the total funding which is the sum of $EQUI$, $CDEP$, $IBDEP$ and $ODEBT$.

Regarding income diversification, this paper considers four types of incomes, including interest income (II), commission income (CI), net profit from other operations ($NPFO$) and other non-interest income ($ONII$). The total operating income (TOI) is the sum of the four types of income. The income diversification is calculated as:

$$IDIV = 1 - \left(\left(\frac{II}{TOI} \right)^2 + \left(\frac{CI}{TOI} \right)^2 + \left(\frac{NPFO}{TOI} \right)^2 + \left(\frac{ONII}{TOI} \right)^2 \right) \tag{9}$$

Our other control variables include Tier 1 regulatory capital ratio, asset growth (the growth rate of total assets), bank size, the nonperforming loan ratio, a crisis dummy (value 1 for two years 2007–2008, 0 otherwise) and two lags of the independent variable. We control these variables because the relation between market power and liquidity may depend on bank characteristics, particularly in the time of crisis. Table 1 presents detail definitions of all variables.

It is likely that our econometric model in Eq. (6) may not include all factors that correlate with the NSFR and the LCR, such as risk preference of each bank. In such a situation, an OLS estimation of the regression model in Eq. (6) would produce biased parameters because of the lagged dependent variables. We employ the generalized method of moments (GMM) for dynamic panel data proposed by Arellano and Bover (1995) and Blundell and Bond (1998) to avoid bias. The GMM procedures allow us to use lagged values of the dependent variable in levels and lagged values of independent variables as instruments. These properties accommodate the possible endogeneity of variables used in our models.

3.4. Data

We obtain accounting information of commercial banks (CBs) and bank holding companies (BHCs) in the U.S. from *Bankscope* database for the period 2000–2015. We focus on data from CBs and BHCs which are not subsidiary banks and use consolidated statements at a higher level as possible.

Initially, we exclude observations with missing and inconsistent values – i.e. negative or zero values – for estimating market power and liquidity measures. Our raw data includes 60,454 bank-year observations of CBs and BHCs in the U.S. for the period 2000–2015. Following Dietrich et al. (2014), we narrow our sample by including only CBs and BHCs which have consistent values of at least 5 consecutive annual observations of liquidity and market power to facilitate the usage of lag dependent and independent variables as instrument variables in GMM regressions. The value of all variables are expressed in millions U.S. dollars and are deflated by 2009 prices. We winsorize all variables at the level of 1 percent of each side for each year to get rid of outliers. Our final sample includes 2665 unique banks with an unbalanced panel data of 27,933 bank-year observations.

The statistical descriptions of our variables are shown in Table 2. On average, a bank has an NSFR of 0.9626, an LCR of 8.4607, a Lerner index of 0.2792, a markup of 0.2456, a tier 1 capital ratio of 14.0102 percent, asset growth of 0.0706, a log asset value of 6.2097, and an NPL of 1.7943 percent.

Table 2
Summary statistics.
Source: Bankscope and authors' calculation.

Variable	N	Mean	Min	P25	Median	P75	Max	STD
LERNER	27,933	0.2792	−0.1500	0.2128	0.2792	0.3472	0.9006	0.1056
Markup	27,933	0.2456	−0.1111	0.1786	0.2500	0.3134	0.8967	0.1084
NSFR	27,933	0.9626	0.7115	0.8681	0.9350	1.0249	2.1612	0.1426
LCR	27,933	8.4607	1.3500	3.9100	6.5000	10.6300	70.3075	7.0489
ADIV	27,933	0.7168	0.0346	0.7118	0.7664	0.7879	0.8237	0.1214
FDIV	27,933	0.2546	0.0486	0.1930	0.2384	0.3002	0.5250	0.0826
IDIV	27,933	0.3261	0.0004	0.2449	0.3200	0.3983	0.5465	0.1024
TIER1 (%)	27,933	14.0102	6.4600	10.7000	12.7000	15.6400	132.0000	5.3722
ASSETGR	27,933	0.0706	−0.9357	−0.0104	0.0339	0.0939	3.3038	0.2232
SIZE	27,933	6.2097	3.5595	5.3181	6.0053	6.8048	10.6033	1.2424
NPL (%)	27,933	1.7943	0.0100	0.4000	0.9000	2.2000	14.6000	2.3893

Notes: This table describes the summary statistics of the variables in Table 1.

4. Empirical analysis

4.1. Baseline results

We estimate the effect of the NSFR on the Lerner index based on Eq. (6) and report the results in Table 3. We employ the OLS estimation method with firm-year fixed effects and bank clustering for Columns 1–4. To control for endogenous issues, we employ GMM techniques (Arellano and Bover, 1995; Blundell and Bond, 1998) for Columns 5–6. The overall results from the baseline regressions support a trade-off between liquidity and market power.

At first, we analyze how the Lerner index correlates with only liquidity in regression (1). Regression results indicate the negative relationship between the Lerner index and the NSFR. The coefficient of the NSFR is −0.1190 which suggests that banks with greater degrees of liquidity are negatively related to bank market power. Relying on the coefficient, we compute its economic effect and find that a one standard deviation increase in the NSFR would lead to a decrease in the Lerner index by 0.1607 times its standard deviation.[3]

Then we examine the correlation between the Lerner index and bank liquidity by adding to regression (1) two lagged values of the Lerner index. We add 1 crisis dummy in regression (2) and add other bank characteristics in regression (3). The coefficients of the NSFR are −0.1060 and −0.1230 in regressions (2) and (3), respectively and are statistically significant at the 1 percent level. Moreover, we also consider whether the relationship is nonlinear by adding the squared value of the NSFR in regression (4). As the coefficient of the quadratic term is not statistically significant, we do not find evidence of a U-shaped relation between the Lerner index and the NSFR.

Besides the OLS models in the regressions (1)–(4), we also employ both one-step and two-step GMM estimations to mitigate endogeneity concern and to account for the dynamic link between liquidity and bank market power. The Wald-test result implies the fitness for the regression model. Hansen test's *p*-value is greater than 10 percent, indicating the validity of the moment restrictions. And the p-values of Arellano–Bond tests support autocorrelation of order 1 but does not support autocorrelation of order 2, confirming the consistency of the GMM estimator. The results of GMM estimation are presented in regressions (5) and (6). Our results from the GMM estimation confirm the results from the OLS estimations which indicate a negative link between the Lerner index and the NSFR. As the NSFR is an inverse proxy for bank-liquidity risk, our results show that banking market power positively correlates with the liquidity risk. This finding is consistent with previous empirical studies that also find a positive correlation between market power and bank risk (Kim, 2018; Leroy and Lucotte, 2017; Schaeck and Cihak, 2014; Tabak et al., 2012).

We have found an inverse relationship between the Lerner index and the NSFR. The finding is supported by the traditional market power-fragility view and the computation of market power and of the NSFR. First, the market power-fragility view posits that banks can use their market power to charge their clients higher lending interest rates. These clients tend to invest in riskier projects which have higher returns than the lending rates because of either the moral hazard problem or adverse selection (Boyd and De Nicolo, 2005; Stiglitz and Weiss, 1981). Riskier projects of the clients increase the risk level of loan portfolios. Second, the negative relationship may originate from two factors: lower revenue and/or higher marginal cost. With regard to revenue, more liquid banks may hold more short-term assets such as cash, deposits at other banks and government bonds. These short-term assets are safer and more liquid but they have lower yields than long-term assets such as loans or investments. Regarding marginal cost, more liquid banks may have to shoulder greater financial costs to achieve stable funding by either holding a higher level of customer deposits or issuing more long-term bonds. The possible combination of lower revenue and higher marginal cost leads to a lower level of bank market power.

The baseline analysis finds a mixed relationship between our control variables and market power in regressions (3) to (6). First, we do not find evidence of a consistent effect of the three diversification variables (ADIV, FDIV, and IDIV), bank

[3] This economic effect is computed by using the coefficient (−0.1190) times the standard deviation of the NSFR (0.1426) and divides by the standard deviation of Lerner index (0.1056).

Table 3
Baseline regression results.

	(1)	(2)	(3)	(4)	(5)	(6)
	LERNER					
	OLS	OLS	OLS	OLS	GMM-1step	GMM-2step
NSFR	**−0.1190*****	**−0.1060*****	**−0.1230*****	**−0.2600*****	**−0.0385*****	**−0.0396*****
	(0.0122)	*(0.0104)*	*(0.0113)*	*(0.0612)*	*(0.0121)*	*(0.0120)*
NSFR^2				0.0516		
				(0.0795)		
ADIV			−0.0076	−0.0027	−0.0041	−0.00418
			(0.0082)	*(0.0086)*	*(0.0087)*	*(0.0089)*
FDIV			0.0073	0.0120	−0.0925***	−0.0916***
			(0.0140)	*(0.0141)*	*(0.0183)*	*(0.0184)*
IDIV			0.0850***	0.0841***	−0.0715***	−0.0713***
			(0.0119)	*(0.0119)*	*(0.0157)*	*(0.0158)*
TIER 1			0.0024***	0.0024***	0.00162***	0.0016***
			(0.0004)	*(0.0004)*	*(0.0005)*	*(0.0005)*
SIZE			0.0134***	0.0126***	−0.0012	−0.0015
			(0.0048)	*(0.0048)*	*(0.0015)*	*(0.0015)*
ASSETGR			0.0046	0.0043	0.0108	0.0108
			(0.0062)	*(0.0062)*	*(0.0109)*	*(0.0110)*
NPL			−0.0060***	−0.0059***	−0.0086***	−0.0086***
			(0.0004)	*(0.0004)*	*(0.0005)*	*(0.0005)*
CRISIS		−0.0649***	−0.0612***	−0.0620***	−0.0670***	−0.0671***
		(0.0026)	*(0.0030)*	*(0.0030)*	*(0.0030)*	*(0.0026)*
L1.LERNER					0.4820***	0.4820***
					(0.0210)	*(0.02110)*
Constant	0.3750***	0.3080***	0.1980***	0.2710***	0.2180***	0.2210***
	(0.0118)	*(0.0109)*	*(0.0315)*	*(0.0456)*	*(0.0179)*	*(0.0170)*
N	27,933	20,077	20,077	20,077	20,077	20,077
Adj. R-sq	0.157	0.270	0.300	0.301		
F-test (p-val.)	186.831(0.000)	267.011(0.000)	201.663(0.000)	194.301(0.000)	232.938(0.000)	236.998(0.000)
AB test AR(1) (p-val.)					−19.662(0.000)	−15.429(0.000)
AB test AR(2) (p-val.)					−1.133(0.257)	−1.002(0.317)
Hansen test (p-val.)					2127.202(0.996)	2127.202(0.996)

This table reports the effect of liquidity risk (NSFR) on bank competition (the Lerner index) via OLS (with bank and year fixed effects and bank clustering) in columns 1–4 and GMM in columns 5–6. Control variables include diversification measures, Tier 1 capital ratio (TIER1), asset growth (ASSETGR), bank size (SIZE), non-performing loan ratio (NPL) and a crisis dummy (CRISIS). Robust standard errors are in brackets. The construction of variables is shown in Table 1. The period covers years 2000–2015.*** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level.
For GMM regression, we use lag 2 of the Lerner index and 4 lags of independent variables (except for CRISIS) as instrumented variables to prevent potential endogeneity of our dependent and independent variables with the residuals. Two standard diagnostic tests for system GMM dynamic model estimations are reported. The first is the Arellano–Bond tests for autocovariance in residuals of order 1 as shown in the AB test AR(1) and of order 2 as shown in the AB test AR(2) with H_0: no autocorrelation. The second is the Hansen test to check for over-identifying restrictions; p-values in brackets.

size, and asset growth on the Lerner index. Second, tier 1 capital ratios have a positive and significant effect on the Lerner index, suggesting that better-capitalized banks acquire greater market power. Third, we find evidence of a negative effect of NPL and the crisis year dummy on the Lerner index. These findings imply that banks with greater credit risk take a higher level of market power and that bank market power reduced in the crisis years 2007 and 2008. Finally, the level of market power remains stable over years as the coefficients of the lagged Lerner index in regressions (5) and (6) are all positive and significant in the regressions.

4.2. Robustness tests

We conduct two robustness tests to examine the validity of the baseline regressions in Section 4.1. We replace the NSFR by the LCR in the first test and then use the price–cost markup instead of the Lerner index in the second. Results of these robustness checks, presented in Tables 4 and 5, yield a consistent relationship between bank liquidity and market power as shown in the baseline analysis.

The coefficients of the LCR in Table 4 are all negative and significant at the 1 percent level across six regressions. These negative coefficients provide evidence that banks with a higher LCR have a lower level of pricing power. On average, the economic effect is considerable since a one standard deviation increase in the LCR produces a decrease in Lerner index by 0.093 times its standard deviation. This economic magnitude is computed by using the coefficient (−0.0014) times the standard deviation of the LCR (7.0489) which is divided by the standard deviation of the Lerner index (0.1056). Among control variables, three diversification variables (ADIV, FDIV, and IDIV), bank size, asset growth, and crisis dummy do not significantly and consistently correlate to the Lerner index. By contrast, tier 1 capital ratio is significantly and positively correlated with the Lerner index and NPL is negatively correlated. The lagged Lerner index has significant and positive coefficients in regression (5) and (6), implying the persistence of the Lerner index.

Table 4
Robustness test 1: the relationship between the LCR and the Lerner index.

	(1)	(2)	(3)	(4)	(5)	(6)
	LERNER					
	OLS	OLS	OLS	OLS	GMM-1step	GMM-2step
LCR	**−0.0014*****	**−0.0014*****	**−0.0013*****	**−0.0016*****	**−0.0007*****	**−0.0008*****
	(0.0002)	*(0.0002)*	*(0.0002)*	*(0.0002)*	*(0.0002)*	*(0.0002)*
LCRˆ2				0.0001		
				(0.0000)		
ADIV			0.0133	0.0146*	0.0053	0.0044
			(0.0082)	*(0.0083)*	*(0.0100)*	*(0.0100)*
FDIV			0.0004	0.0004	−0.0996***	−0.1010***
			(0.0138)	*(0.0138)*	*(0.0211)*	*(0.0213)*
IDIV			0.0816***	0.0815***	−0.0831***	−0.0844***
			(0.0119)	*(0.0119)*	*(0.0172)*	*(0.0173)*
TIER 1			0.0013***	0.0013***	0.0014***	0.0014***
			(0.0003)	*(0.0003)*	*(0.0004)*	*(0.0004)*
SIZE			0.0128***	0.0126***	−0.0014	−0.0016
			(0.0047)	*(0.0047)*	*(0.0020)*	*(0.0020)*
ASSETGR			0.0050	0.0050	0.0140	0.0134
			(0.0064)	*(0.0064)*	*(0.0121)*	*(0.0121)*
NPL			−0.0063***	−0.0063***	−0.0087***	−0.0087***
			(0.0004)	*(0.0004)*	*(0.0005)*	*(0.0005)*
CRISIS		−0.0629***	−0.0574***	−0.0577***	−0.0731***	−0.0541***
		(0.0026)	*(0.0029)*	*(0.0029)*	*(0.0031)*	*(0.0030)*
L1.LERNER					0.4520***	0.4530***
					(0.0214)	*(0.0214)*
Constant	0.2740***	0.2170***	0.0956***	0.0971***	0.2060***	0.1890***
	(0.0024)	*(0.0041)*	*(0.0301)*	*(0.0301)*	*(0.0204)*	*(0.0201)*
N	27,933	20,077	20,077	20,077	20,077	20,077
Adj. R-sq	0.150	0.266	0.295	0.295		
F-test (p-val.)	184.249(0.000)	260.880(0.000)	198.272(0.000)	190.908(0.000)	188.911(0.000)	197.815(0.000)
AB test AR(1) (p-val.)					−18.711(0.000)	−15.016(0.000)
AB test AR(2) (p-val.)					−1.502(0.133)	−1.339(0.181)
Hansen test (p-val.)					1987.687(0.479)	1987.687(0.479)

This table reports the effect of the LCR on the Lerner index via OLS (with bank and year fixed effects and bank clustering) in columns 1–4 and GMM in columns 5–6. Control variables include diversification measures, Tier 1 capital ratio (TIER1), asset growth (ASSETGR), bank size (SIZE), non-performing loan ratio (NPL), and a crisis dummy (CRISIS). Robust standard errors are in brackets. The construction of variables is shown in Table 1. The period covers years 2000–2015. *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level.
For GMM regression, we use lag 2 of the Lerner index and 4 lags of independent variables (except for CRISIS) as instrumented variables to prevent potential endogeneity of our dependent and independent variables with the residuals. Two standard diagnostic tests for system GMM dynamic model estimations are reported. The first is the Arellano-Bond tests for autocovariance in residuals of order 1 as shown in the AB test AR(1) and of order 2 as shown in the AB test AR(2) with H0: no autocorrelation. The second is the Hansen test to check for over-identifying restrictions; p-values in brackets.

Table 5 reports results of another robustness test with the same main independent variable, NSFR, as in Table 3 but with a different dependent variable, the markup instead of the Lerner index. The NSFR in all regressions generates negative and significant coefficients, implying a negative correlation between the NSFR and bank market power. A one standard deviation increase in the NSFR indicates a decrease in the markup by 0.1789 times its standard deviation. The economic effect is calculated by using the coefficient (−0.1360) times the standard deviation of the NSFR (0.1426) divided by the standard deviation of the markup (0.1084). Similar to the baseline analysis, NPL and the lagged values of the market power are both significant and consistent.

The results of the correlation between bank liquidity and market power so far are based on the winsorization of the financial variables to remove outliers as normally used in the area of banking competition and risk (Anginer et al., 2014; Kim, 2018). We also relax the winsorization in robustness tests as suggested by an anonymous reviewer. The finding relying on non-winsorized data is similar to the one with winsorized data. For brevity, we do not report the results for the robustness, but will provide them upon request.

5. How to mitigate the negative impact of greater liquidity?

In Section 4, we have shown that there is a trade-off between liquidity and market power. In this section, we are interested in investigating how a bank can mitigate the negative correlation between liquidity and market power. To answer this question, we consider how the correlation varies with bank characteristics via the following regression equation:

$$\begin{aligned} market\ power_{i,t} = {} & \beta_1 \times liquidity_{i,t} + \beta_2 \times bank\_characteristic_{i,t} \\ & + \beta_3 \times liquidity_{i,t} \times bank\_characteristic_{i,t} + X_{i,t}\beta \\ & + \alpha_i + \lambda_t + \varepsilon_{i,t} \end{aligned} \tag{10}$$

Table 5
Robustness Test 2: the relationship between the NSFR and Markup.

	(1)	(2)	(3)	(4)	(5)	(6)
	MARKUP					
	OLS	OLS	OLS	OLS	GMM-1step	GMM-2step
NSFR	**−0.1360*****	**−0.1150*****	**−0.1300*****	**−0.2500*****	**−0.0529*****	**−0.0536*****
	(0.0129)	*(0.0111)*	*(0.0118)*	*(0.0631)*	*(0.0142)*	*(0.0141)*
NSFRˆ2				0.0560*		
				(0.0303)		
ADIV			−0.0088	−0.0044	−0.0064	−0.0061
			(0.0084)	*(0.0088)*	*(0.0123)*	*(0.0123)*
FDIV			0.0074	0.0118	−0.0841***	−0.0826***
			(0.0146)	*(0.0147)*	*(0.0219)*	*(0.0222)*
IDIV			0.0889***	0.0880***	−0.0962***	−0.0962***
			(0.0123)	*(0.0123)*	*(0.0179)*	*(0.0178)*
TIER 1			0.0026***	0.0025***	0.0020***	0.0020***
			(0.0004)	*(0.0004)*	*(0.0005)*	*(0.0005)*
SIZE			0.0381***	0.0374***	0.0116***	0.0115***
			(0.0050)	*(0.0050)*	*(0.0024)*	*(0.0024)*
ASSETGR			0.0101*	0.0097	0.0082	0.0085
			(0.0061)	*(0.0061)*	*(0.0133)*	*(0.0135)*
NPL			−0.0065***	−0.0065***	−0.0098***	−0.0098***
			(0.0004)	*(0.0004)*	*(0.0006)*	*(0.0006)*
CRISIS		−0.0639***	−0.0652***	−0.0659***	0.1090***	0.1100***
		(0.0028)	*(0.0031)*	*(0.0031)*	*(0.0212)*	*(0.0207)*
L1.MARKUP					0.4370***	0.4360***
					(0.0217)	*(0.0216)*
Constant	0.3370***	0.2980***	0.0365	0.1000**	0	0
	(0.0125)	*(0.0115)*	*(0.0323)*	*(0.0471)*	*(.)*	*(.)*
N	27,933	20,077	20,077	20,077	20,077	20,077
Adj. R-sq	0.133	0.230	0.270	0.271		
F-test (p-val.)	174.515(0.000)	203.720(0.000)	165.231(0.000)	159.226(0.000)	4548.730(0.000)	4263.397(0.000)
AB test AR(1) (p-val.)					−19.194(0.000)	−15.225(0.000)
AB test AR(2) (p-val.)					−1.455(0.146)	−1.308(0.191)
Hansen test (p-val.)					1970.856(0.579)	1970.856(0.579)

This table reports the effect of the NSFR on the markup via OLS (with bank and year fixed effects and bank clustering) in columns 1–4 and GMM in columns 5–6. Control variables include diversification measures, Tier 1 capital ratio (TIER1), asset growth (ASSETGR), bank size (SIZE), non-performing loan ratio (NPL), and a crisis dummy (CRISIS). Robust standard errors are in brackets. The construction of variables is shown in Table 1. The period covers years 2000–2015. *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level.
For GMM regression, we use lag 2 of the markup and 4 lags of independent variables (except for CRISIS) as instrumented variables to prevent potential endogeneity of our dependent and independent variables with the residuals. Two standard diagnostic tests for system GMM dynamic model estimations are reported. The first is the Arellano-Bond tests for autocovariance in residuals of order 1 as shown in the AB test AR(1) and of order 2 as shown in the AB test AR(2) with H0: no autocorrelation. The second is the Hansen test to check for over-identifying restrictions; p-values in brackets.

The dependent variable is individual bank market power, captured by the Lerner index and the mark-up. Liquidity is captured by the NSFR or the LCR. Bank characteristic is one of the following: diversification, equity capital ratio, assets growth, bank size, and nonperforming loan ratio. $X_{i,t}$ includes the remaining control variables of Eq. (6). We employ the OLS estimation method for Eq. (10).

We include one interaction between liquidity and one of bank characteristics such as diversification, equity capital ratio, assets growth, bank size, and nonperforming loan ratio in Eq. (10) because it is possible that there may exist different influences on market power of diversification, the equity capital ratio, assets growth, bank size and the nonperforming loan ratio. For example, more diversified banks can have a higher proportion of liquid assets, and thus have a higher NSFR and LCR. High capitalized banks are likely to obtain a lower marginal cost due to their better liquidity. Similarly, large banks and fast-growing banks are likely to derive a lower marginal cost due to their greater economies of scale. Banks with a higher level of credit risk (proxied by NPL ratio) have to set aside a higher provision for loan loss, which ultimately may result in lower revenue. In sum, adding interaction terms between liquidity and bank characteristics allows us to find the joint correlation (marginal effect) of liquidity and bank characteristics on market power.

The results of two regression specifications of Eq. (10) are presented in Table 6. First, we use the NSFR as a proxy for bank liquidity. The regression results are displayed in columns (1)–(4). Second, we use the LCR as an alternative proxy for bank liquidity and their regression outcomes are presented in columns (5)–(8). The coefficients for control variables in columns (1)–(8) are suppressed for brevity.[4] We still find a negative correlation between liquidity (NSFR and LCR) and the Lerner index. The result supports our finding of the negative correlation between liquidity and market power (as shown in

[4] The coefficients of the interaction terms between the three diversification variables and liquidity are not reported in Table 6 and 8 for brevity because these coefficients are not significant.

Table 6
The interactive effect of liquidity and bank characteristics on the Lerner index.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	LERNER							
NSFR	−0.1210***	−0.1450***	−0.2330***	−0.1430***				
	(0.0154)	*(0.0106)*	*(0.0470)*	*(0.0111)*				
LCR					−0.0010***	−0.0012***	0.00001	−0.0009***
					(0.0002)	*(0.0001)*	*(0.0007)*	*(0.0002)*
NSFR * TIER1	−0.0012							
	(0.0008)							
NSFR * ASSETGR		**0.0373***						
		(0.0203)						
NSFR * SIZE			0.0149*					
			(0.0076)					
NSFR * NPL				0.0012				
				(0.0025)				
LCR * TIER1					−0.0001			
					(0.0000)			
LCR * ASSETGR						**0.0007****		
						(0.0003)		
LCR * SIZE							−0.0002*	
							(0.0001)	
LCR * NPL								−0.0001***
								(0.0001)
N	37,085	37,085	37,085	37,085	37,084	37,084	37,084	37,084
Adj. R-sq	0.190	0.190	0.190	0.190	0.180	0.180	0.180	0.181

This table reports the effects of the NSFR or the LCR and its interaction with one of bank characteristics such as bank liquidity (NSFR), Tier 1 capital ratio (TIER1), asset growth (ASSETGR), bank size (SIZE), and non-performing loan ratio (NPL) on the Lerner index via OLS (with bank and year fixed effects and bank clustering). Other control variables are those used in Table 3 and are suppressed for brevity. Because there are 3 diversification measures and 2 liquidity measures and the coefficients of the interactions between liquidity measures and diversification measures are not significant at any conventional level, we do not tabulate the results for diversification measures. Robust standard errors are in brackets. The construction of variables is shown in Table 1. The period covers years 2000–2015. *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level.

Table 7
The interactive effect of liquidity and bank characteristics on the markup.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	MARKUP							
NSFR	−0.1340***	−0.1600***	−0.2760***	−0.1560***				
	(0.0161)	*(0.0110)*	*(0.0477)*	*(0.0115)*				
LCR					−0.0011***	−0.0013***	−0.0005	−0.0009***
					(0.0003)	*(0.0002)*	*(0.0007)*	*(0.0002)*
NSFR * TIER1	−0.0013							
	(0.0009)							
NSFR * ASSETGR		**0.0480****						
		(0.0198)						
NSFR * SIZE			0.0198***					
			(0.0076)					
NSFR * NPL				0.0010				
				(0.0026)				
LCR * TIER1					−0.0001			
					(0.0000)			
LCR * ASSETGR						**0.0008****		
						(0.0003)		
LCR * SIZE							−0.0001	
							(0.0001)	
LCR * NPL								−0.0002***
								(0.0001)
N	37,085	37,085	37,085	37,085	37,084	37,084	37,084	37,084
adj. R-sq	0.190	0.191	0.191	0.190	0.179	0.180	0.179	0.180

This table reports the effects of the NSFR or the LCR and its interaction with one of bank characteristics such as bank liquidity (NSFR), Tier 1 capital ratio (TIER1), asset growth (ASSETGR), bank size (SIZE), and non-performing loan ratio (NPL) on the markup via OLS (with bank and year fixed effects and bank clustering). Other control variables are those used in Table 3 and are suppressed for brevity. Because there are 3 diversification measures and 2 liquidity measures and the coefficients of the interactions between liquidity measures and diversification measures are not significant at any conventional level, we do not tabulate the results for diversification measures. Robust standard errors are in brackets. The construction of variables is shown in Table 1. The period covers years 2000–2015. *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level.

Section 4). The negative correlation refers to the dark side of greater liquidity. Banks tend to reduce their market power to be safer.

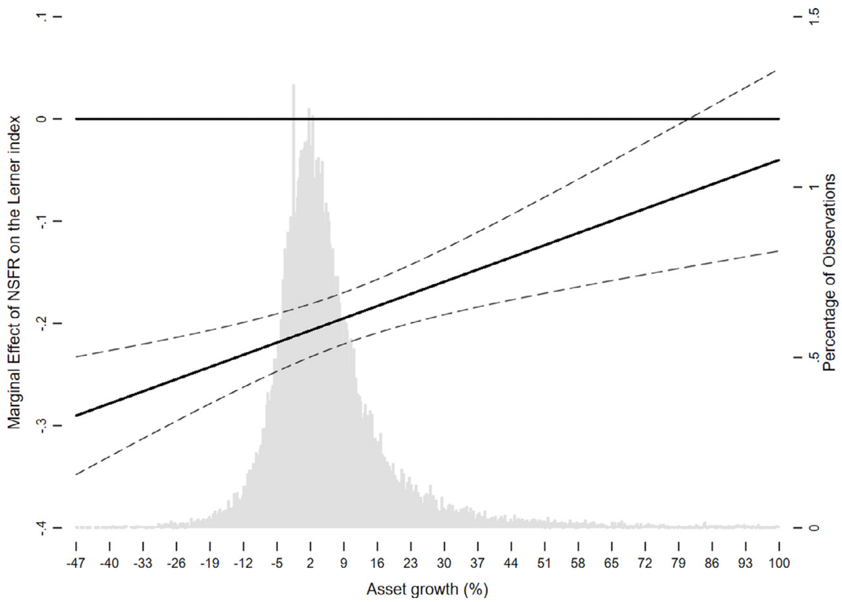

Fig. 1. Marginal effect of the NSFR on the Lerner index.

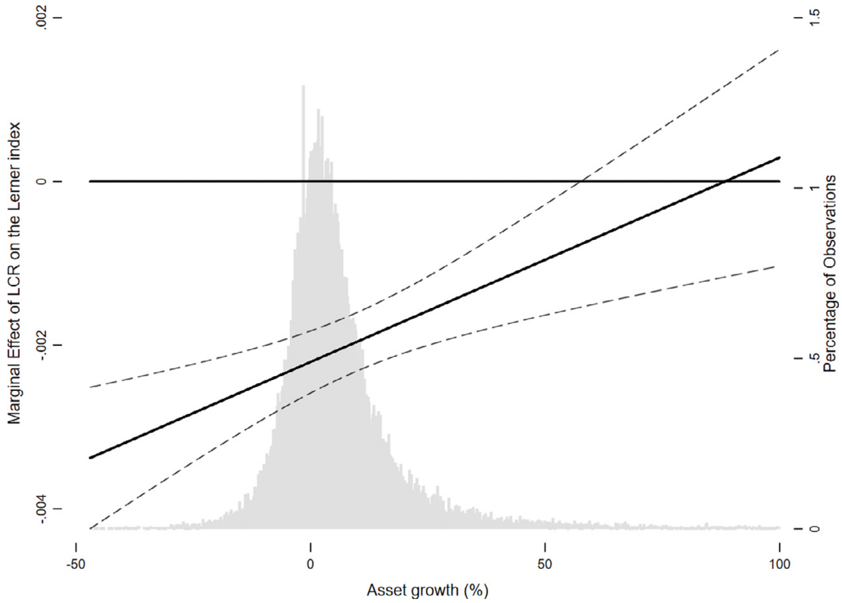

Fig. 2. Marginal effect of the LCR on the Lerner index.

In this section, we focus more on the joint and interactive effects of both liquidity and bank characteristics on market power. We find that the only interaction between liquidity (NSFR and LCR) and asset growth is positive and significant as shown at regression 2 and 6 in Table 6. This positive interaction has an important economic meaning for both bank managers and regulators. Bank managers can mitigate the negative effect of liquidity on market power by having more aggressive growth strategies. This can partially explain why banks have become bigger after the Global Financial Crisis in 2007–08. For policy makers, banks which continue to become bigger can cause concerns on systemic risk. So, imposing higher liquidity standards may potentially create other types of bank risk in the future.

We also check the robustness of the interaction between liquidity and asset growth by using markup, an alternative indicator of market power. Table 7 represents a positive and significant interaction, confirming a bright side of greater liquidity. On the one hand, lower growth banks can typically generate lower revenue. On the other hand, higher growth

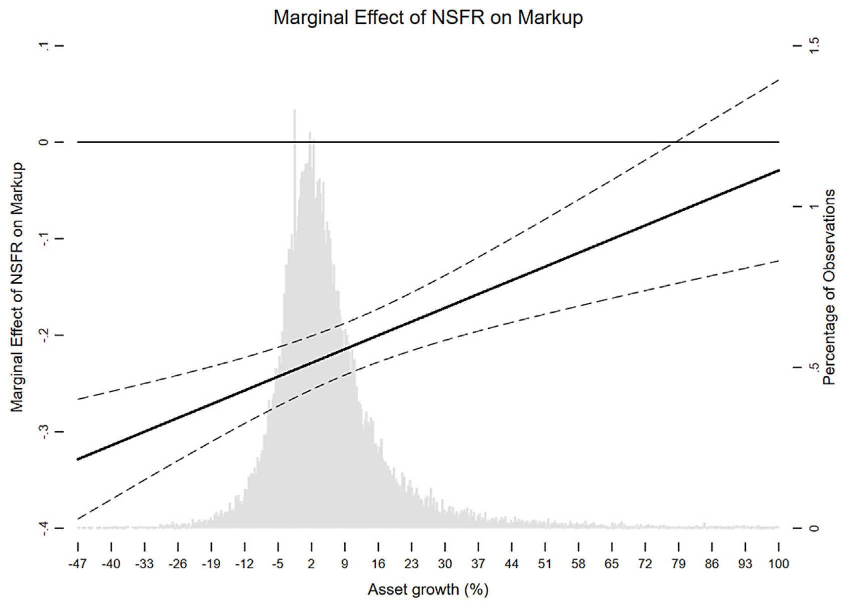

Fig. 3. Marginal effect of the NSFR on Markup.

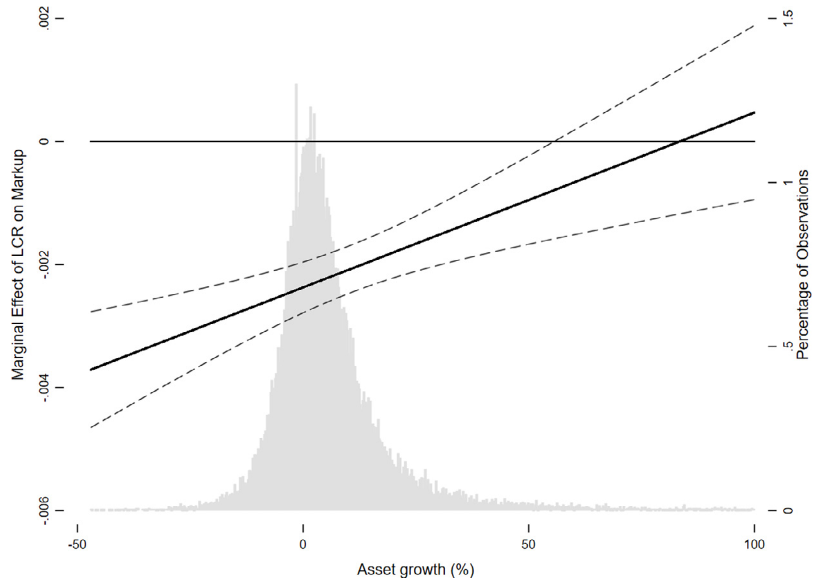

Fig. 4. Marginal effect of the LCR on Markup.

banks on average yield more revenue and enjoy lower marginal cost (due to economies of scale and scope). Put differently, rapidly growing banks are more likely to gain market power simultaneously with asset expansion.

We plot the marginal effect (fitted coefficient) of liquidity on market power over the observed range of asset growth in Figs. 1–4 to more deeply examine the relationship. Figs. 1–4 plot the marginal effect (fitted coefficient) of liquidity on the observed range of asset growth in our sample. The solid line corresponds with the estimated linear relationship and the dotted lines represent the 95 percent confidence bounds. Even though the solid lines in the two figures are upward sloping, these solid lines lie below 0. The results have three implications. First, banks can mitigate the negative effect of liquidity on market power by accelerating the speed of expansion. Second, when banks are required to apply a greater level of liquidity, the banking sector will tend to grow overall. And finally, controlling for the interaction between liquidity and asset growth also supports an aggregate negative relationship between liquidity and market power as presented in Section 4.

6. Conclusion

Bank supervisors pay attention to liquidity shortage as it is seen as an important driver of the recent financial crisis in 2007–08. To prevent similar shocks, the BASEL III Accord requires individual banks to maintain higher liquidity. This raises an important concern: how will an increase in liquidity affect bank market power? Our investigation of 2,665 unique CBs and BHCs in the U.S. during 2000–2015 shows a cost of being safer in term of liquidity: banks may have to face lower market power. The result is robust over three dimensions: (1) the two alternative market power measures, including the Lerner index and mark-up, (2) two liquidity measures, namely net stable funding ratio and the liquidity coverage ratio, and (3) OLS and GMM (one-step and two-step) estimations. In addition, through an examination of the joint effect of liquidity and bank characteristics, this paper shows a bright side of greater liquidity. Fast growing banks may be able to mitigate the cost of being safer in the new regulatory environment of Basel III.

One limitation of this study is that it ignores ownership structure and corporate governance practices. Future work could analyze the association between liquidity and market power conditional on the ownership structure and corporate governance practices. The conditional effect may have further interesting implications for bank managers and policymakers. In this regard, this paper's limitations present avenues for future research.

Acknowledgments

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Appendix A

This table reports estimated coefficients of a translog cost function based on the estimation of Eq. (1). The dependent variable is the natural logarithm of the normalized total costs (normalized total costs, $\widetilde{TC}_{it}$, is the sum of interest expenses and non-interest expenses scaled by $W_{1,it}$). Q_{it} is total output and is proxied by total assets. $W_{1,it}$ is funding costs (proxied by the ratio of interest expenses to total assets). $\tilde{W}_{2,it}$ is labor costs (proxied by the normalized ratio of personnel expenses to total assets). $\tilde{W}_{3,it}$ is other operating costs (proxied by the normalized ratio of administrative and other operating expenses to total assets). *Trend* stands for time trend which accounts for technological change. The subscripts i and t denote each bank and year respectively. We estimate the regression using stochastic frontier analysis (SFA) with bank clustering. Robust standard errors are used. The period covers the years 2000–2015.

	SFA	
	Parameter	p-value
$\log(Q_{it})$	0.7064	0.000
$\frac{1}{2}\times(\log(Q_{it}))^2$	0.0449	0.000
$\log\left(\tilde{W}_{2,it}\right)$	−0.0850	0.002
$\log\left(\tilde{W}_{3,it}\right)$	−0.0734	0.001
$\log(Q_{it})\times\log\left(\tilde{W}_{2,it}\right)$	0.0157	0.000
$\log(Q_{it})\times\log\left(\tilde{W}_{3,it}\right)$	−0.0094	0.006
$\log\left(\tilde{W}_{2,it}\right)\times\log\left(\tilde{W}_{3,it}\right)$	0.0030	0.634
$\frac{1}{2}\times\left(\log\left(\tilde{W}_{2,it}\right)\right)^2$	0.0560	0.000
$\frac{1}{2}\times\left(\log\left(\tilde{W}_{3,it}\right)\right)^2$	0.0109	0.064
Trend	−0.0529	0.000
$Trend^2$	0.0024	0.000
$Trend\times\log(Q_{it})$	0.0074	0.000
$Trend^2\times\log(Q_{it})$	−0.0006	0.000
α	−1.7559	0.000
σ_u	15.9374	0.000
σ_v	0.1900	0.000
λ	83.9042	0.000

Appendix B

This table shows the definition of variables available from the *Bankscope* database and explains how these variables are calculated to estimate translog cost function in this study.

Variable	Series
Total deposits	DATA2030
Personnel expenses	DATA10150
Total assets	DATA2025
Overheads	DATA2090
Fixed assets	DATA2015
Total interest expense	DATA10070
Total non-interest expenses	DATA10170
Total non-interest operating income	DATA10140
Gross interest and dividend income	DATA10040
Price of deposits	Total interest expense/total deposits
Price of labor	Personnel expenses/total assets
Price of physical capital	(Overheads − personnel expenses)/fixed assets
Total cost	Total interest expense + total non-interest expenses
Total revenue	Gross interest and dividend income + total non-interest operating income
Bank type	ENTITYTYPE
Bank index	BVDIDNUM
Time index	CLOSDATE_YEAR

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