Does liquidity regulation affect commercial banks' carbon bias? Evidence from China

ABSTRACT

This study demonstrates the influence mechanisms of liquidity regulation on bank carbon bias through a simplified balance sheet model. Subsequently, we empirically analyze the impact of regulatory liquidity pressure on bank carbon bias by using a sample of 213 Chinese commercial banks from 2009 to 2019. We find that liquidity regulation, which has a significant positive impact on bank carbon bias, accounts for a 23% increase in the sample banks' aggregated carbon bias before and after the implementation due to the slow pace of decarbonization. Further, this effect becomes smaller when banks have lower initial reliance on stable funding or a lower capital adequacy ratio, and it is mainly found in state-owned, joint-stock, and urban commercial banks; banks with assets of no less than ¥200 billion; and during economic upturn periods. The main findings remain consistent after considering bank proactive liquidity management.

JEL classifications: G21; G28; Q56

Keywords: Liquidity regulation; Commercial bank; Banks' lending behavior; Carbon bias

1. Introduction

The market value weighted index, which is commonly used as a benchmark for active investment strategies in portfolio investment, may not be sufficient to reflect the "average" economy. Thus, investments that track market indices may exhibit carbon bias, which can be defined as the relative difference in the total carbon intensity between the market index and the real economy (Doda, 2018). Similarly, the relative difference in the total carbon intensity between bank loan portfolios and the real economy can be used to measure the carbon bias of bank lending decisions.[1] In 2012, China implemented the Green Credit Guidelines that aim to curb industrial pollution by financially penalizing polluters. They require banks to restrict lending to non-green firms and provide financial support for environmentally friendly firms. Since then, the former China Banking and Insurance Regulatory Commission (CBIRC) and the People's Bank of China have actively promoted banks' low-carbon transition from the perspective of guidance, statistics, and evaluation, while gradually establishing a comprehensive green finance policy framework.[2] Despite the

[1] For simplicity, the term "carbon bias" refers to the carbon bias of banks' lending behavior unless otherwise specified.

[2] The agency is re-organized in 2023 and renamed to National Financial Regulatory Administration.

remarkable progress driven by policies in the Chinese banking sector's green governance and the real economy's low-carbon transition, we still observe an obvious downward deviation of bank loan portfolios' carbon intensity from that of the real economy. As shown in Fig. 1, the average carbon bias of the banking sector did not exhibit a downward trend after 2012 and has instead shown an upward trend since 2014. This phenomenon indicates that there are other fundamental factors hindering a faster low-carbon transition in the banking sector.

(a) Individual bank (b) Average

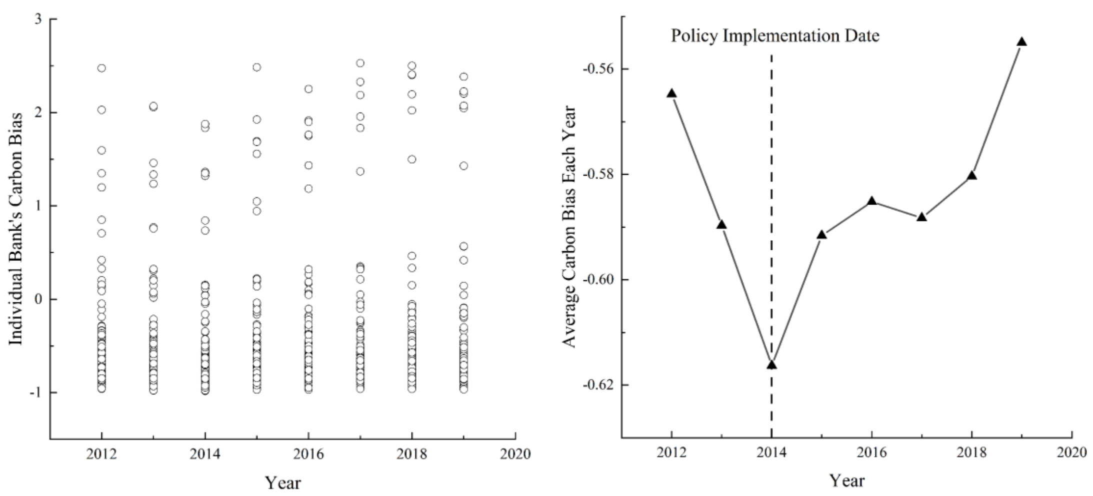

Fig. 1. The trend of bank carbon bias.
Notes: (a) Carbon bias of individual banks from 2012 to 2019;
(b) average carbon bias of all sample banks from 2012 to 2019.

Although postcrisis bank liquidity regulation plays an important role in maintaining financial stability, it can also result in some unintended economic consequences (Roberts et al., 2023). Evidence suggests that the current liquidity regulation contains an intrinsic carbon bias, which seems to promote short-term brown investments at the expense of more long-term, climate-friendly investments (Campiglio, 2016). Specifically, liquidity regulation may dampen banks' willingness to lend to green and low-carbon projects (D'Orazio and Popoyan, 2019). Furthermore, the effect of liquidity regulation on bank lending behavior has already been verified by several studies on, for example, loan volume adjustment (Ananou et al., 2021; Sharma and Chaunhan, 2023) and loan structure adaption (Ananou et al., 2021; Banerjee and Mio, 2018). Therefore, the potential link between liquidity regulation and bank carbon bias is an interesting topic.

The first strand of closely related literature emphasizes that bank liquidity management and liquidity regulation can cause changes in balance sheet liquidity levels and adjustments in asset and liability items. DeYoung and Jang (2016) empirically examine the liquidity management of United

States (U.S.) banks prior to the implementation of Basel III and find that most banks would actively manage their balance sheet liquidity positions by setting liquidity targets and quickly adjusting balance sheet items to fill a gap when they were not meeting their targets. Banerjee and Mio (2018) use the Individual Liquidity Guidance to study the impact of United Kingdom liquidity regulation on bank balance sheets and show that banks respond to tighter regulation by increasing high-quality liquid assets (HQLA) and nonfinancial deposits, as well as reducing interbank loans and short-term wholesale funding. De Bandt et al. (2021) suggest that banks' liquidity increases when the regulatory constraint is binding because the banks will hoard extra liquidity, while they do not if the constraint is not binding. Focusing on banks' lending behavior, the impact of liquidity regulation on loan volume adjustment or loan structure adaption is relatively little studied compared to capital regulation. For example, Sharma and Chaunhan (2023) examine the impact of Basel III liquidity regulation on bank lending in developing economies and show that bank lending is positively affected by the liquidity coverage ratio (LCR) and negatively impacted by the net stable funding ratio (NSFR). Ananou et al. (2021) explore the impact of liquidity regulation on bank lending by introducing the Dutch Liquidity Balance Rule (LBR) of 2003 as a setting and find that it increased Dutch banks' loan volume relative to that of other euro area banks and also affected the loan composition (with corporate and retail lending increasing more than mortgage lending) and the maturity profile of loan portfolios. As far as we know, no previous research has directly investigated the impact of liquidity regulation on the sectoral distribution of bank loans.

The second strand of closely related literatures focuses on the carbon bias that usually exists in portfolio investments. Several studies have indirectly illustrated the presence of carbon bias in financial markets via carbon premiums and carbon α. Bolton and Kacperczyk (2021) explore the impact of carbon emissions on U.S. stock returns and find that the stocks of firms with higher total CO_2 emissions (and changes in emissions) earn higher returns, which cannot be explained through differences in unexpected profitability or other known risk factors. Meanwhile, In et al. (2019) suggest that a portfolio comprising long positions in carbon-efficient stocks and short positions in carbon-inefficient stocks generates positive and statistically significant abnormal returns, meaning that carbon α in portfolio investment reflects the underpricing of carbon risk in financial markets. Cosemans and Schoenmaker (2022) measure carbon bias by studying the difference in carbon intensity between the market index and the real economy and indicate that it exists in popular value-weighted stock market indices tracked by U.S. and European index funds and exchange-traded funds. Boermans and Galema (2020) calculate the carbon bias as the differential between the weight of domestic portfolios and the weight of domestic market capitalization in the global portfolio and find that European investors exhibit evident carbon home bias. Overall, this body of literature focuses on the conflict between institutional investors' preferences for sustainable investment and the existence of carbon bias in investment practices. Similarly, how much carbon bias influences banks' lending behavior, as documented in financial markets, remains a research gap.

Using a simplified balance sheet model, this study demonstrates that tighter liquidity regulation leads to an increase in bank carbon bias through two channels: reducing asset profitability and increasing financing costs. Subsequently, we empirically analyze the impact of regulatory liquidity pressure on bank carbon bias by using a sample of 213 Chinese commercial banks from 2009 to 2019. There are several key findings. First, liquidity regulation has a significant positive impact on bank carbon bias, accounting for a 23% increase in the sample banks' aggregated carbon bias before and after the implementation. This is mainly due to the slow pace of bank loan decarbonization, rather than the slow promotion of low-carbon development. Second, when banks have lower initial stable funding reliance or a lower capital adequacy ratio, the impact of liquidity regulation on bank carbon bias correspondingly becomes smaller. Third, this impact is mainly found in state-owned, joint-stock, and urban commercial banks; banks with assets of no less than ¥200 billion; and during economic upturn periods. Fourth, the baseline results remain consistent after taking bank proactive liquidity management into account.

This paper has three significant contributions. First, we contribute to the literature on the unintended consequences of liquidity regulations influenced by the spillover effect from the environment. We show positive impacts on exacerbating banks' carbon bias, incremental to the findings of prior studies focused on lower lending and output (Roberts et al., 2023; BIS, 2021) or conflicts with other policies in the fragmented regulatory system (Sundaresan and Xiao, 2018). Second, we contribute to the literature that has investigated the impact of liquidity regulation on bank behavior from the sectoral distribution of bank loans. Prior studies have mainly focused on how banks respond to liquidity pressure by shrinking balance sheets or adjusting their composition of loan portfolios toward shorter maturities without changing balance sheet size (DeYoung and Jang, 2016; Banerjee and Mio, 2018; Ananou et al., 2021). However, we show that liquidity regulations may incentivize banks to increase lending to high-carbon industries due to rising funding costs and declining profitability, a behavior not fully explained by traditional strategies such as shrinking balance sheets or favoring shorter-maturity loans. Third, we add to the growing literature on the carbon bias of portfolio investment in financial markets. While existing studies provide useful insights on the carbon bias in institutional investors' equity portfolio practices (Bolton and Kacperczyk, 2021; Boermans and Galema, 2020; In et al., 2019), we show that similar carbon bias is also prevalent in banks' loan portfolio decisions.

The rest of the paper is organized as follows. Section 2 introduces the institutional background.

Section 3 constructs a theoretical model to examine how liquidity regulation affects banks' carbon bias. Section 4 develops hypotheses from previous studies and our theoretical model. Section 5 outlines the research design. Sections 6 presents the empirical results and further discussion. Section 7 concludes the paper with policy implications.

2. Institutional background

The liquidity regulation of Chinese commercial banks basically adheres to Basel III. After the Basel Committee on Banking Supervision (BCBS) first introduced the LCR and NFSR in 2009, the China Banking Regulatory Commission (CBRC) incorporated them into the existing liquidity supervision indicator system in February 2010. Following the final standards issued by the BCBS in December 2010, the CBRC released *Guiding Opinions on the Implementation of New Regulatory Standards in China's Banking Industry (Yinjianfa [2011] No. 44)*, stipulating that the LCR and NSFR should be implemented from January 2012 and requiring covered banks' LCRs and NSFRs to achieve 100% before the end of 2013 and 2016, respectively. Referring to the draft issued by the BCBS in 2013, the CBRC released *Rules on Liquidity Risk Management of Commercial Banks (For Trial Implementation) (Yinjianhuiling [2014] No. 2)*, effective from March 2014, which further detailed the transitional arrangements and the scope of application for the LCR, while temporarily removing content related to the NSFR. It sets a five-year transition period during which the LCRs of covered banks should reach 60%, 70%, 80%, and 90%, respectively, before the end of the first four years and 100% before the end of 2018. Following the final draft of the NSFR issued by the BCBS in 2014, the CBIRC released *Rules on Liquidity Risk Management of Commercial Banks (Yinbaojianhuiling [2018] No. 3)* in 2018. These rules formally incorporated the NSFR and expanded the scope of its application while also establishing stricter transitional arrangements for the LCR. According to this document, both the LCR and NSFR are regulatory compliant for commercial banks with assets of no less than ¥200 billion. However, banks that fail to meet this standard shall apply these two indicators with the approval of the banking regulatory authority. Moreover, the LCR should be no lower than 90% during the transition period, while the NSFR should reach 100% before the end of 2018 with no transition period. The development process of Chinese commercial banks' liquidity regulation is summarized in Appendix A1.

In addition to the background information already shared, it is important to acknowledge the potential biases in our estimations due to the presence of other contemporaneous policies affecting bank liquidity. These policies include, but are not limited to, *Deposit Insurance Regulation (Guowuyuanling [2015] No. 660)*, *Guiding Opinions on Regulating the Asset Management Business of Financial Institutions (Yinfa [2018] No. 106)*, and the removal of the loan-to-deposit ratio (LDR) limit in 2015.

3. Theoretical model

We assume that banks can observe lower short-term realized returns on low-carbon loans than on high-carbon loans. Therefore, they need to make a trade-off between long-run (i.e., internalizing long-term carbon risks and increasing lending to low-carbon sectors) and short-run (i.e., maximizing short-term profits and increasing lending to high-carbon sectors) operational objectives. However, liquidity regulation, which is designed to dampen banks' asset-liability maturity mismatches, could upset this balance and further alter the allocation of loans to high- or low-carbon sectors. In this section, we consider two types of liquidity risks, asset-side solvency (Goldstein and Pauzner, 2005) and liability-side bank runs (Diamond and Dybvig, 1983), and examine the impact of liquidity regulation (i.e., the LCR and NFSR) on individual banks' loan allocation decisions in terms of carbon using a simplified balance sheet model.

3.1 LCR

We assume that banks raise external funding by issuing equity e and short-term deposits d to invest in risky, illiquid loans l and HQLA m. For d and m, returns are exogenously determined by R^d and R^m, respectively. Thus, the balance sheet equation can be expressed as $e+d=l+m$. Specifically, loans l are composed of low-carbon loans l^L and high-carbon loans l^H and are subject to $l^H / l^L = \delta$, where δ represents bank carbon bias. The short-term realized returns of loans to high- and low-carbon sectors upon maturity are R^l and R^l / α ($\alpha > 1$), respectively, where R^l refers to the random returns upon maturity. Note that banks need to bear the cost of early loan liquidation, that is, a certain proportion λ of cash flows regarding due loans.

Banks subject to capital constraints $e=\phi(l^H+\alpha l^L+\psi m)$ should maintain a minimum proportion of equity to risk-weighted assets ϕ, where the risk weight of loans is normalized to one ; α and ψ denote the relative risk weight set by the observed realized returns between low- and high-carbon loans and the risk weight of HQLA, respectively. Meanwhile, banks are also constrained by the LCR, which can be expressed as $m=\theta d$, where θ refers to the minimum HQLA to short-term liabilities ratio that they should retain. The ϕ, ψ, and θ are all regulatory parameters.

Given the balance sheet equation and capital and LCR constraints, we can easily confirm that banks will issue loans in proportion to their equity, as shown in Eq. (1):

$$e=\phi\frac{(\delta+\alpha)(1-\theta)+\psi\theta(1+\delta)}{(\phi\psi\theta+1-\theta)(1+\delta)}l=\hat{\phi}l\,, \tag{1}$$

where $\hat{\phi} > \phi$ illustrates that banks have built capital buffers for HQLA m and risky loans l. Note that $e = \phi[(\delta+\alpha)/(1+\delta)]l = \phi(\delta+\alpha)l^L = \phi(1+\alpha/\delta)l^H$ holds when $\psi = 0$. In internal risk management practices, banks will build higher capital buffers for short-term, riskier low-carbon loans than for high-carbon ones, which can be written as $\hat{\phi}^L > \hat{\phi}^H$ with $\hat{\phi}^L = \phi(\delta+\alpha) > \phi$ and $\hat{\phi}^H = \phi(1+\alpha/\delta) > \phi$. This implies that $\delta > 1$, that is, that banks prefer to issue high-carbon loans when equity is provided, thereby further leading to carbon bias. In addition, Eq. (1) also indicates a relatively large impact from LCR regulatory parameter θ on capital buffers, which further affects a bank's total loan volume.[3]

Without panic-based runs, banks will choose a proper δ to earn positive net profits. Otherwise, negative net profits will raise concerns about the banks' solvency positions and further result in a liquidity crisis. The critical value of δ is given by Eq. (2):

$$\frac{\delta}{1+\delta}R^l l + \frac{1}{(1+\delta)\alpha}R^l l + R^m m - R^d d = 0\,. \tag{2}$$

The solution for Eq. (2) yields $\bar{\delta}$. On this basis, the impact of the LCR regulatory parameter θ on bank carbon bias $\bar{\delta}$ can be described as $d\bar{\delta}/d\theta \propto [(1-\phi\psi)R^d - R^m]$. When $R^m < (1-\phi\psi)R^d$ (i.e., the return on HQLA is lower than the deposit interest rates to a certain proportion), $d\bar{\delta}/d\theta > 0$ holds, meaning that banks tend to raise the proportion of high-carbon loans in response to the tighter LCR requirement so as to avert liquidity crises triggered by bank failures. The reason lies in the fact that the low-yield HQLA held due to LCR constraints damages banks' asset profitability, thereby prompting them to issue more high-carbon loans to retain their profits at origination. Consequently, the tighter LCR regulation can lead to an increase in bank carbon bias by reducing asset profitability.

With panic-based runs, banks will choose a proper δ to ensure that the early liquidation of loans can satisfy the needs of some depositors to withdraw their deposits prematurely. Otherwise, despite hoarding sufficient capital, banks will still suffer from self-fulfilling panic runs as defined in Diamond and Dybvig (1983). The critical value of δ with panic-based runs is given by Eq. (3):

$$\frac{\alpha\delta+1}{\alpha}R^l(1-\lambda)l + R^m m = R^d \chi d\,, \tag{3}$$

where χ is the ratio of early deposit withdrawals to total deposits. The solution for Eq. (3) yields $\tilde{\delta}$. When $\delta \in (\bar{\delta}, \tilde{\delta})$, banks still face underlying risk of runs despite their solvency. The impact of the LCR regulatory parameter θ on bank carbon bias δ can be described as $d\tilde{\delta}/d\theta \propto [(1-\phi\psi)\chi R^d - R^m]$. In Case 1, when there is a relatively low proportion of early deposit withdrawal χ and $R^m > (1-\phi\psi)\chi R^d$, $d\tilde{\delta}/d\theta < 0$ holds. At this point, the effect leads to a shorter

[3] We can confirm that $d\hat{\phi}/d\theta > 0, d\hat{\phi}/d\psi > 0$, meaning that the larger the LCR constraints or the higher the risk weight of HQLA, the more capital buffers banks need to build, which further leads them to curtail lending.

interval of $(\bar{\delta}, \tilde{\delta})$, and the banks' choices of δ are mainly constrained by the lower limit $\bar{\delta}$, which increases as θ rises. In Case 2, when there is a relatively high proportion of early deposit withdrawal χ and $R^m < (1-\phi\psi)\chi R^d$, $d\tilde{\delta} / d\theta > 0$ holds. In this situation, the effect is similar to that without bank runs, except that it is the upper limit $\tilde{\delta}$, which increases with the rise in θ and mainly constrains the banks' choices of δ. This implies that, in comparison to the case without runs, banks will further raise their proportion of high-carbon loans to avert runs, but this will be done at the cost of a deeper deterioration in asset profitability arising from holding lower-yield HQLA.

3.2 NSFR

We assume that banks raise external funding by issuing equity e, short-term deposits d, and long-tern debts b to invest in risky, illiquid loans l,[4] where b refers to stable funding (i.e., funding that cannot be withdrawn at any time and is immune to bank runs). The interest rate of long-term debt R^b is higher than that of short-term deposit R^d (i.e., $R^b > R^d$). Thus, the balance sheet equation can be expressed as $e + d + b = l$. On the one hand, banks are subject to capital constraints $e = \phi\left(l^H + \alpha l^L\right)$, and on the other hand, they are constrained by the NSFR, which can be expressed as $e + b \geq vl$, requiring their stable funding $e + b$ to be at least v fraction of their illiquid loans l. Note that the composition of bank loans is the same as defined above; R^b is exogenously given and v is the regulatory parameter.

Without panic-based runs, banks will choose a proper δ to avoid failures. The critical value of δ is shown in Eq. (4):

$$\frac{\delta}{1+\delta} R^l l + \frac{1}{(1+\delta)\alpha} R^l l - R^b b - R^d d = 0 . \tag{4}$$

The solution for Eq. (4) yields $\bar{\delta}'$. The impact of the NSFR regulatory parameter v on bank carbon bias $\bar{\delta}'$ can be described as $d\bar{\delta}' / dv \propto (R^b - R^d)$. When $R^b > R^d$ (i.e., the long-term financing cost is higher than the short-term deposit cost), $d\bar{\delta}' / dv > 0$ holds, meaning that banks tend to raise the proportion of high-carbon loans to avert failures when confronted with the tighter NSFR requirement. The reason lies in the fact that long-term stable funding, retained due to NSFR constraints, increases banks' financing costs, thereby prompting them to issue more high-carbon loans to ensure positive net profits. Consequently, the tighter NSFR regulation can lead to an increase in bank carbon bias by increasing financing costs.

With panic-based runs, banks will choose a proper δ to ensure that the early liquidation of loans can satisfy the needs of some depositors to withdraw their deposits prematurely. The critical

[4] For simplicity, we examine the impact of the LCR and NSFR on bank carbon bias one by one, rather than adding them to our theoretical model simultaneously.

value of δ with panic-based runs is given by Eq. (5):

$$\frac{\alpha\delta+1}{\alpha(1+\delta)}R^{l}(1-\lambda)l=\chi R^{d}(1-v)l\,. \tag{5}$$

The solution for Eq. (5) yields $\tilde{\delta}'$. When $\delta\in(\bar{\delta}',\tilde{\delta}')$, banks still face underlying risk of runs despite their solvency. The impact of the NSFR regulatory parameter v on bank carbon bias $\tilde{\delta}'$ can be described as $d\tilde{\delta}'/dv\propto(1-\alpha)(1-\lambda)<0$. At this point, the effect can lead to a shorter interval of $(\bar{\delta}',\tilde{\delta}')$, and the banks' choices of δ are primarily constrained by the lower limit $\bar{\delta}'$, which increases as v rises. This is because banks have to substitute volatile short-term deposits with stable liabilities so as to comply with the NSFR regulation, which in turn alleviates their internal fragility.

Our theoretical analysis offers three main insights. First, if banks can observe lower realized returns on low-carbon loans than on high-carbon ones, they need to build higher capital buffers for the former, thereby leading to a preference for high-carbon sectors in short-term loan decisions when equity is given. Second, both the LCR and NFSR tend to reduce bank profitability, which under certain conditions[5] can exacerbate liquidity risks arising from the banks' decreased solvency. To cope with the reduction in profitability under the liquidity regulation, banks prefer to raise the proportion of short-term high-yield, high-carbon loans. Therefore, the tighter liquidity regulation can lead to an increase in bank carbon bias through two channels, namely, reducing asset profitability and increasing financing costs. Finally, if the yield on HQLA is far lower than the deposit interest rate, the LCR may prompt banks to further raise their proportion of high-carbon loans to avert the risk of runs. Overall, the policy instruments aimed at preventing liquidity risks may have an unintended impact on banks' short-term loan allocation decisions. In other words, the tighter liquidity regulation may result in an increase in bank carbon bias.

4. Hypotheses development

The theoretical model in Section 2 demonstrates that tighter liquidity regulation leads to an increase in bank carbon bias through two channels: reducing asset profitability and increasing financing costs. We can formally elaborate these two channels as mechanisms. The first is the profit target mechanism. Bank's profit target may be in conflict with increasing the proportion of HQLA and reducing the degree of asset-liability mismatch (Diamond and Kashyap, 2016; Roberts et al., 2023), thereby potentially resulting in an increase in the proportion of high-carbon loans with higher short-term expected yields. The second is the financing cost mechanism. Under liquidity regulation, banks may be compelled to use high-cost stable funding to finance long-term low-carbon loans.

[5] For the LCR, banks will face profit erosion as long as the yield on their HQLA is lower than a certain proportion of the deposit interest rate. For the NSFR, the same case will happen as long as the financing costs of stable funding are higher than that of deposits.

This would make banks more sensitive to temporary maturity mismatches between assets and liabilities (D'Orazio and Popoyan, 2019), thereby reducing their financing budget and the proportion of low-carbon loans. If the theoretical model is predicting correctly, we expect that the regulatory-induced liquidity pressure will have a positive correlation with carbon bias before and after the implementation due to the aforementioned two mechanisms. Therefore, we propose the following hypothesis:

H1. After the implementation of liquidity regulation, the corresponding liquidity pressure can lead to an increase in bank carbon bias.

The carbon bias defined in this study comprises two main components: weight difference (the wedge between the sector weights in loans and in the real economy) and sectoral carbon intensity difference. During the low-carbon transition, an increase in carbon bias may arise from either the slower decline in the share of high-carbon loans or the slower growth in the share of low-carbon loans when compared to the respective shares in the real economy. If the regulatory-induced liquidity pressure indeed leads to an increase in bank carbon bias, one may inquire whether this causality is primarily driven by high-carbon or low-carbon loans. The former reflects sluggish decarbonization in bank loans, while the latter indicates insufficient promotion of low-carbon development in bank loans. To answer this, we propose two additional hypotheses based on H1:

H1a. After the implementation of liquidity regulation, the corresponding liquidity pressure can lead to an increase in the bank carbon bias of high-carbon loans.

H1b. After the implementation of liquidity regulation, the corresponding liquidity pressure can lead to an increase in the bank carbon bias of low-carbon loans.

Banks encounter a risk-return trade-off dilemma in their assets and liabilities when complying with the liquidity regulation. For example, banks that hold sufficient liquid assets are likely to see an increase in the value of their current portfolios due to a decrease in fire-sale risks, but this occurs at the cost of lower future asset returns (Diamond and Kashyap, 2016). This implies that how banks make adjustments on the asset side in response to the liquidity regulation may depend on their initial (i.e., pre-implementation) reliance on stable funding (Roberts et al., 2023). Banks with high initial reliance on stable funding may adjust their liquidity ratios by reducing available stable funding (ASF) and increasing required stable funding (RSF), and they tend to adequately increase the proportion of riskier assets to pursue profitability if they already meet regulatory requirements (Z. Jin et al., 2022). However, banks with low initial reliance on stable funding may tend to do the opposite because they have more scope to satisfy liquidity requirements by increasing long-term stable funding rather than adjusting asset structure or cutting loans (Roberts et al., 2023). Thus, we expect that the lower the initial reliance on stable funding, the smaller the impact of regulatory-induced liquidity pressure on bank carbon bias. The hypothesis in question is as follows:

H2. Banks with lower initial reliance on stable financing will experience a smaller impact from the regulatory liquidity pressure on carbon bias.

The interaction between capital and liquidity regulations has received widespread attention (Acosta-Smith et al., 2019; De Bandt et al., 2021; Kim and Sohn, 2017), with a consensus that the two regulations appear as substitutes to some extent. Therefore, the impact of liquidity regulation on carbon bias may depend on a bank's initial capital adequacy ratio, corresponding to two scenarios (i.e., high and low). Banks with high initial capital adequacy ratios face a trade-off between the "skin in the game" effect and the "stable funding structure" effect (Acosta-Smith et al., 2019), respectively, incentivizing them to accumulate more liquid assets to ensure sufficient capital and invest in higher-yielding illiquid assets. In other words, banks can choose to make adjustments on either the funding structure in liabilities or the risk-return structure in assets. However, banks with low initial capital adequacy ratios are strongly motivated to adjust the liability funding structure and replenish the capital to simultaneously attain joint regulatory compliance and reduce liquidity risk associated with solvency. Thus, we expect that the lower the initial capital adequacy ratio, the smaller the impact of regulatory-induced liquidity pressure on bank carbon bias. The pertinent hypothesis is as follows:

H3. Banks with a lower initial capital adequacy ratio will experience a smaller impact from the regulatory liquidity pressure on carbon bias.

5. Research design

5.1 Variables and data

5.1.1 Bank carbon bias

We measure bank carbon bias in three steps outlined by Cosemans and Schoenmaker (2022). First, we aggregate carbon emissions from economic activities to corresponding sectors based on the *Industrial Classification for National Economic Activities (GB/T 4754-2017)*.[6] Then we divide the sectoral carbon emissions by the corresponding gross value added (GVA) to obtain the sectoral carbon intensity (see Eq. (6)).

[6] The correspondence between economic activities and sectors is detailed in Appendix A2.

$$sector\_intensity_{i,t} = \frac{carbon\ emissions_{i,t}}{gross\ value\ added_{i,t}}, \tag{6}$$

where $carbon\ emission_{i,t}$ and $gross\ value\ added_{i,t}$, respectively, represent the carbon emissions and GVA of sector i in year t.

Second, we use the sectoral loan share of each bank and the sectoral GVA share of each province or municipality as weights to calculate the weighted average carbon intensity, thus respectively obtaining the loan carbon intensity and the economic carbon intensity (see Eqs. (7) and (8)).

$$loan\_intensity_{j,t} = \sum \frac{loan_{i,j,t}}{total\ loan_{j,t}} \times sector\_intensity_{i,t}, \tag{7}$$

$$economy\_intensity_{k,t} = \sum \frac{gross\ value\ added_{i,k,t}}{gross\ value\ added_{k,t}} \times sector\_intensity_{i,t}, \tag{8}$$

where $sector\_intensity_{i,t}$ represents the carbon intensity of sector i in year t and $total\ loan_{j,t}$, $loan_{i,j,t}$, $gross\ value\ added_{k,t}$ and $gross\ value\ added_{i,k,t}$ represent the total loans of bank j in year t, its loans to sector i, the total GVA of province or municipality k where bank j was headquartered in year t, and its GVA to sector i, respectively.[7]

Finally, we define the loan carbon bias of each bank as the relative difference between its loan carbon intensity and the economic carbon intensity of its headquarter province or municipality (see Eq. (9)).

$$loan\_bias_{j,t} = \frac{loan\_intensity_{j,t} - economy\_intensity_{k,t}}{economy\_intensity_{k,t}}, \tag{9}$$

where $loan\_intensity_{j,t}$ and $economy\_intensity_{k,t}$, respectively, represent the loan carbon intensity of bank j in year t and the economic carbon intensity of province or municipality k in year t.

5.1.2 Bank liquidity pressure

Following Luo et al. (2020) and Z. Jin et al. (2022), we use the changes in the NSFR before and after the implementation of liquidity regulation to measure banks' liquidity pressure,[8] with larger changes indicating greater pressure. The NSFR is the ratio of ASF to RSF, and it measures the banks' medium and long-term liquidity. ASF and RSF are conversion values of commercial

[7] Given the concentration of total assets in a small portion of national or regional sample banks, we faced a trade-off in measuring banks' carbon bias at different economic carbon intensity levels and ultimately compromised by using the provincial (municipal) rather than the national level for two reasons: (1) 91.5% of our sample banks primarily operate within their headquarter provinces or municipalities, and (2) evident variations exist in carbon emissions across provinces (municipalities).

[8] We do not use the LCR for three reasons: (1) LCR calculation requires substantial assumptions, and the indispensable internal data is not available. (2) The LCR is a short-term regulatory ratio (within 30 days), thus not suitable for our analysis of medium and long-term balance sheet items. (3) The LCR is consistent with the NFSR since short-term changes in the LCR ultimately accumulate into long-term changes in the NFSR (Diamond and Kashyap, 2016).

banks' on- and off-balance sheet items, as shown in Eq. (10). To classify the items, we first construct a stylized balance sheet of Chinese commercial banks following Vazquez and Federico (2015). Then we identify the specific items necessary for the ASF and RSF calculation in line with the China Banking Database (CBD). Moreover, we primarily assign the weights using two official documents (i.e., *Basel III: the net stable funding ratio* and *Rules on Liquidity Risk Management of Commercial Banks (Yinbaojianhuiling [2018] No. 3)*) as benchmarks while also referring to Gobat et al. (2014) and DeYoung and Jang (2016).[9] See Appendix A3 for the detailed calculation approach.

$$NSFR = \frac{ASF}{RSF} = \frac{\sum_i w_i L_i}{\sum_j w_j A_j}, \tag{10}$$

where L_i, A_j, w_i, and w_j represent liability and equity items, asset and off-balance sheet items, and the given weight of corresponding items, respectively.

5.1.3 Control variables

We isolate the liquidity regulation effects on bank carbon bias by controlling for bank-specific, time-varying characteristics in profitability and safety. Following Sharma and Chauhan (2023), we include the return on assets (ROA) and the ratio of noninterest income to total income (NII) to control for profitability, with these items representing banks' earning capacities and business models, respectively. Following Naceur et al. (2018) and Roberts et al. (2023), we include the capital adequacy ratio (CAR) and the ratio of nonperforming loans to total loans (NPL) as key measures for safety, with these items capturing banks' solvency and credit risks, respectively. Furthermore, we include the bank size (BS) to account for the inherent differences in lending behavior between large and small banks, following Banerjee et al. (2018) andAnanou et al. (2021). We lag all control variables one period to avoid simultaneity.

5.1.4 Data

Limited by data availability, this paper employs a sample of 213 Chinese commercial banks from 2009 to 2019,[10] including 6 state-owned commercial banks, 12 joint-stock commercial banks, 103 urban commercial banks, and 92 rural commercial banks. The sample period begins with 2009 and ends in 2019 so as to avoid the interference of the 2008 US financial crisis and the COVID-19 pandemic starting from 2020, respectively. The data on bank sectoral loans, balance sheets, and control variables are obtained from the CBD,[11] while the sectoral carbon emissions and GVA data

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[9] The BCBS made continuous improvements to the NSFR calculation method from 2009 to 2010 and published the final draft in 2014. Gobat et al. (2014) and DeYoung and Jang (2016) provide two rare studies in the currently available literature that complete calculations based on BCBS (2014).

[10] The data limitation primarily lies in the sectoral loan data. Nonetheless, this database remains the largest publicly available. To ease the impact of the missing and abnormal values, all bank-specific variables except bank size are winsorized at the 1% and 99% level. Notably, our sample of 213 commercial banks, representing on average 91.41% of total Chinese banking sector assets, could effectively capture the overall characteristics of Chinese commercial banks. For more details, please refer to Appendix A4.

[11] The CBD, a newly constructed database encompassing more than 1,000 Chinese banks over the past two decades, is to our knowledge

used in this study are respectively obtained from the Carbon Emission Accounts and Datasets (CEADs) and the National Bureau of Statistics.[12] Table 1 presents the variable definitions and descriptive statistics.

Table 1

Variable definitions and descriptive statistics.

	Definition	*N*	Mean	SD	Min	Max
CB	Bank carbon bias	1,988	-0.583	0.461	-0.982	2.529
NSFR	Net stable funding ratio	1,917	1.292	0.665	0.008	3.509
LP	Liquidity pressure	1,917	0.812	0.796	0.000	3.509
BS	Natural logarithm of average end-of-period asset balance between current and last year (i.e., bank size)	1,766	11.591	1.688	7.496	17.180
ROA(%)	Return on assets	1,761	1.034	0.431	0.058	2.306
NII(%)	Ratio of noninterest income to total income	1,850	20.439	18.710	-1.088	84.687
CAR(%)	Capital adequacy ratio	1,887	13.512	2.346	8.840	23.420
NPL(%)	Ratio of nonperforming loans to total loans	1,871	1.549	0.973	0.050	6.520

Note: All bank-specific variables except bank size are winsorized at the 1% and 99% levels.

5.2 Model specifications

Following Nunn and Qian (2011), we use a continuous measure of bank liquidity pressure as a proxy for the intensity of treatment. There are no untreated sample banks because the first formal liquidity regulation released in 2014 treats all commercial banks equally. Therefore, we use the same date of initial implementation for all the sample banks. Our estimation strategy follows the same logic as a standard differences-in-differences strategy; that is to say, we compare the relative change in bank carbon bias in the post-implementation period relative to the pre-implementation period across banks with different liquidity pressure. This allows us to capture two sources of variation in the treatment variable. The first variation arises from the differences in post-implementation liquidity pressure within and across banks. The second variation arises from the pre-post differences in the liquidity pressure of all banks.

The above estimation strategy has two advantages. First, the continuous measure of treatment fits well with the liquidity regulation implementation practice in China (i.e., the feature of gradual improvements and transition arrangements). Second, when there are no untreated units, we prefer

the most comprehensive micro-level banking database in China, surpassing the coverage of other popular ones including Bankfocus, Wind, and China Stock Market and Accounting Research (CSMAR). This database has already been used in published studies (e.g., Ge et al., 2023).

[12] CEADs data source: https://www.ceads.net/data.

to believe that "among those treated, timing of treatment is as good as random," rather than the assumption that "control units tell us the counterfactual over-time changes" (Miller, 2023).

Based on the estimation strategy, we examine the impact of liquidity pressure on carbon bias after the implementation date as follows:

$$CB_{j,t} = \beta LP_{j,t} + Control_{j,t-1} + \mu_j + \mu_t + \xi_{j,t}\,, \tag{11}$$

where $CB_{j,t}$ denotes the carbon bias of bank j in year t. The key explanatory variable is $LP_{j,t}$, which equals the liquidity pressure of bank j in year t for the years 2014 onward and 0 otherwise.[13] β is the coefficient of interest, which represents the impact of liquidity pressure on bank carbon bias after the implementation date. If the coefficient is significantly positive, it indicates that the larger liquidity pressure in the post-implementation period significantly increases bank carbon bias relative to the pre-implementation period and vice versa. μ_j and μ_t are bank fixed effects and year fixed effects, respectively, allowing us to control for time-invariant, bank-specific characteristics related to carbon bias and various macroeconomic changes—such as credit demand, economic growth, policy interest rates, and so on. $Control_{j,t-1}$ are a set of time-variant bank-specific variables. α is the constant term and $\xi_{j,t}$ is the error term. Additionally, the standard errors are clustered at the bank level, suggesting that they are autocorrelated within banks but not across banks.

To further examine the sensitivity of treatment effect on initial conditions (i.e., H2 and H3), we extend Eq. (11) by including the interaction terms of $LP_{j,t}$ to banks' initial reliance on stable funding and the capital adequacy ratio, as shown in Eq. (12):

$$CB_{j,t} = Dep_{j,pre} + \beta LP_{j,t} + \beta_1 Dep_{j,pre} \times LP_{j,t} + Control_{j,t-1} + \mu_j + \mu_t + \xi_{j,t}\,, \tag{12}$$

where $Dep_{j,pre}$ is a grouping dummy variable, which equals 1 for banks with below median initial values and 0 otherwise, respectively, referring to $SF\_Dep_{j,pre}$ and $CAR_{j,pre}$ (i.e., grouping the dummy variable of initial reliance on stable funding and the capital adequacy ratio). The coefficients of the interaction terms are of interest, and we expect them to be negative and significant if the hypotheses hold.

We estimate the average treatment effect in Eq. (11), assuming that it is time invariant and homogeneous across banks. However, as Goodman-Bacon (2021) points out, two-way fixed effects may result in negative weights when ignoring the heterogeneous treatment effect across periods and units. Thus, we relax the assumption by allowing the time-variant treatment, as shown in Eq. (13):

[13] The LCR and NSFR should be effective from January 2012, as outlined in *Guiding Opinions on the Implementation of New Regulatory Standards in China's Banking Industry (Yinjianfa [2011] No. 44)* proposed by the CBRC; however, this is not a formal release. Instead, it is *Rules on Liquidity Risk Management of Commercial Banks (For Trial Implementation) (Yinjianhuiling [2014] No. 2)*, enforced in March 2014, that really serves as a constraint, and since then relatively larger banks have also started to calculate these two ratios. Please note that we do not take 2014 as the implementation date for granted. Rather, we find it consistent with our data through empirical analysis conducted later in this study.

$$CB_{j,t} = \sum_{l} \beta_l \cdot LP_{j,t}^{l} + A_j + B_t + Control_{j,t-1} + \mu_j + \mu_t + \xi_{j,t} , \quad (13)$$

where l is the distance between year t and the implementation date, and all the other variables are defined as in Eq. (11). The vector of $\{\beta_l\}$ is of interest, revealing the correlation between the liquidity pressure and bank carbon bias in each time period. It is important to note that we are not focused on the absolute level. Instead, we are particularly interested in the pattern over time. More specifically, we expect to observe a discontinuity in the pattern initially around the implementation date and then to see that all the pre-implementation coefficients are not significantly different from 0. If this is so, the validity of our chosen implementation date and the critical parallel trend assumption can be confirmed.

6. Empirical results

6.1 Baseline estimates

Table 2 provides the baseline estimation results. Column (1) only controls for bank and year fixed effects, while column (2) also includes multiple time-variant, bank-specific characteristics. The results confirm our H1 that banks have experienced significant increase in carbon bias due to their larger liquidity pressure for the period after implementation, which remains large and significant even after bank-specific variables (i.e., BS, ROA, NII, CAR, and NPL) are included. Furthermore, we perform a straightforward computation on the magnitude of the estimated effect by measuring the extent to which the observed pre-post increase in bank carbon bias can be explained by liquidity pressure. Our computation proceeds in three steps. First, we use the coefficient of liquidity pressure in column (2) to calculate the counterfactual (i.e., if not subject to the liquidity regulation) carbon bias for each bank year during 2014–2019. This calculation equals each bank's carbon bias minus the product of its pre-post changes in the NSFR and the treatment effect. Then we multiply them with their corresponding carbon emissions for that year (i.e., $(CB_{j,t} - \hat{\beta} \times LP_{j,t}) \times carbon\ emissions_t$, $t = 2014, 2015, ..., 2019$) and finally obtain the annual aggregated counterfactual carbon bias by summing up each year's carbon bias measured by carbon emissions.

Table 2

Bank liquidity pressure and carbon bias.

	(1)	(2)
LP	0.0274*** (3.4808)	0.0277*** (3.6760)
BS		-0.1480** (-2.4479)

	(1)	(2)
ROA		0.0111 (0.5501)
NII		-0.0012** (-2.4847)
CAR		0.0009 (0.2550)
NPL		-0.0128 (-0.6808)
Constant	-0.6041*** (-94.6137)	1.1446 (1.5722)
Bank FE	YES	YES
Year FE	YES	YES
Observations	1,917	1,462
Within R^2	0.0067	0.0624

Notes: The *t*-statistics are reported in the parentheses, and all the control variables are lagged one period. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively. The control variables include the bank size (*BS*), the return on assets (*ROA*), the ratio of noninterest income to total income (*NII*), the capital adequacy ratio (*CAR*), and the ratio of nonperforming loans to total loans (*NPL*).

Fig. 2 plots the actual and counterfactual evolution of bank carbon bias over the period 2010–2019. For sample banks, the actual mean aggregated carbon bias before the implementation (i.e., during 2010–2013) is -1,688.7 Mt, while the actual and its corresponding counterfactual outcomes are -1,525.1 and -1,562.6 Mt after the implementation (i.e., during 2014–2019), respectively. This indicates that the aggregated carbon bias would have increased 126.1 Mt (i.e., to 77% of the actual outcome) around 2014 if the regulation had not taken place. In other words, our result can explain 23% of the pre-post variation in bank carbon bias.

(a) Aggregated carbon bias each year

(b) Average aggregated carbon bias

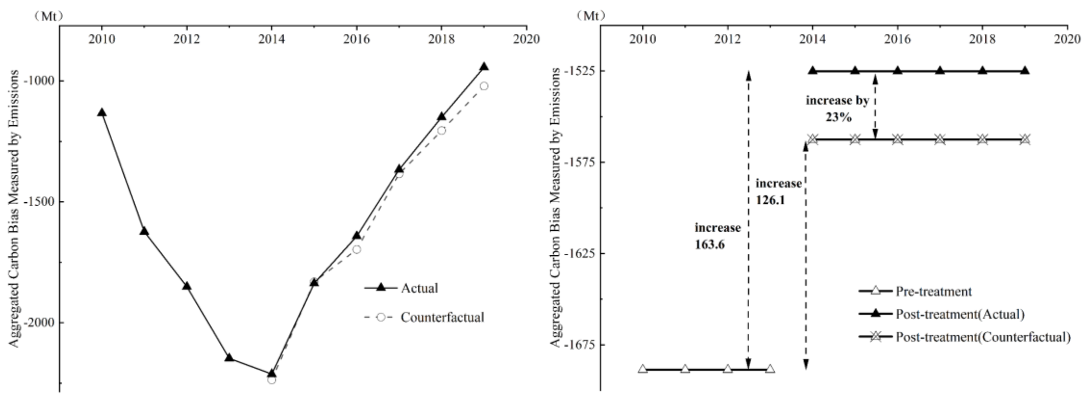

Fig. 2. Actual and counterfactual evolution of sample banks' total carbon bias.

Notes: Panel (a) plots the sample banks' aggregated carbon bias during the period 2010–2019, where the solid line corresponds to the actuals, while the dashed line is the counterfactuals. Panel (b) plots the pre-post differences in the mean values of aggregated carbon bias, with pre- and post-period referring to 2010–2013 and 2014–2019, respectively. The average pretreatment actual evolution is represented by the sold line with hollow triangles, and the average post-treatment actual and counterfactual evolution are represented with the filled triangles and the hollow triangles with crosses, respectively.

Table 3 reports the results of H1a and H1b obtained from reestimating Eq. (11) using further disaggregated bank carbon bias based on three different division criteria of high- and low-carbon sectors.[14] As shown in columns (1) to (4), we find that liquidity pressure after the implementation is significantly positive to the bank carbon bias of high-carbon loans at the 1% level (i.e., confirming our H1a) but that it is significantly negative to that of low-carbon loans at the 5% or 10% level (i.e., rejecting our H1b). Our estimates are robust on the bank carbon bias of high- or low-carbon loans under different classifications because both the signs and sizes of the coefficients remain consistent. The aforementioned results suggest that the positive effect mainly comes from the bank carbon bias of high-carbon loans, while that of low-carbon loans decreases as regulatory-induced liquidity pressure increases during the sample period. Therefore, we can attribute this to the sluggish decarbonization of, rather than the insufficient promotion of low-carbon development in, bank loans. On the one hand, this is consistent with the reality that banks lack the motivation to provide funding for energy conservation and emission reduction projects in high-carbon sectors, which mostly involve capacity investments, production equipment transformation and upgrading, governance infrastructure construction and installation, and so forth, due to the relatively large initial investment scale, low yields, and the long recovery period (Lu and Fang, 2018). On the other hand, this also largely aligns with China's green credit policy in practice, with its original aim not only to curb the expansion of high-pollution and high-energy-consuming sectors but also, more importantly, to guide credit ultimately toward supporting the development of green sectors (Li et al., 2023).

Table 3

Bank liquidity pressure and carbon bias of high- and low-carbon sectors.

	High-carbon sectors		Low-carbon sectors	
	(1)	(2)	(3)	(4)
Panel A.				

[14] In column (1), we draw on W. Jin et al. (2022) and take the median of sectoral carbon emissions as a cutoff point. Specially, we classify the "manufacturing," "production and supply of electricity, heat, gas and water," and "transportation, storage and post" as high-carbon sectors, while the "agricultural, forestry, animal husbandry and fishery," "mining," "construction," and "wholesale and retail trades" are classified as low-carbon sectors. The full details on the median value and classification of high-carbon sectors for each year are provided in Appendix A5. In column (2), following Zhou et al. (2017), we classify the "mining," "manufacturing," "production and supply of electricity, heat, gas and water," and "transportation, storage and post" as high-carbon sectors, while the "agricultural, forestry, animal husbandry and fishery," "construction," and "wholesale and retail trades" are classified as low-carbon sectors. In column (3), following Yan and Chen (2017), we classify the "mining," "manufacturing," "production and supply of electricity, heat, gas and water," "construction," and "transportation, storage and post" as high-carbon sectors, while the "agricultural, forestry, animal husbandry and fishery" and "wholesale and retail trades" are classified as low-carbon sectors.

LP	0.0288***	0.0296***	-0.0192	-0.0303**
	(3.5247)	(3.7680)	(-1.5573)	(-2.4912)
Observations	1,917	1,462	1,917	1,462
Within R^2	0.0068	0.0610	0.0017	0.0226
Panel B.				
LP	0.0279***	0.0282***	-0.0425**	-0.0364**
	(3.5068)	(3.6955)	(-2.2868)	(-2.2147)
Observations	1,917	1,462	1,917	1,462
Within R^2	0.0068	0.0628	0.0034	0.0161
Panel C.				
LP	0.0278***	0.0281***	-0.0377	-0.0334*
	(3.5019)	(3.6937)	(-1.5722)	(-1.7046)
Observations	1,917	1,462	1,917	1,462
Within R^2	0.0068	0.0625	0.0017	0.0114
Controls	NO	YES	NO	YES
Bank FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Notes: The *t*-statistics are reported in the parentheses, and all the control variables are lagged one period. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively. The control variables include the bank size (*BS*), the return on assets (*ROA*), the ratio of noninterest income to total income (*NII*), the capital adequacy ratio (*CAR*), and the ratio of nonperforming loans to total loans (*NPL*).

6.2 Moderating effect

Table 4 presents the results of H2 and H3 by considering the role of bank initial conditions (i.e., reliance on stable funding and the capital adequacy ratio), as shown in columns (1)–(2) and (3)–(4), respectively. The interaction terms $SF\_Dep \times LP$ and $CAR\_dum \times LP$ are significantly negative at the 1% and 10% levels, respectively, thus verifying H2 and H3. Our findings illustrate that the treatment effect is highly sensitive to the abovementioned conditions and becomes smaller at the lower initial level. More specifically, the respective coefficient estimates are 0.0460 and 0.0056 when SF_Dep equals 0 and 1, respectively, while they are 0.0341 and 0.0131 for CAR_dum in the same situations.

Table 4

Moderating effect results.

	Reliance on stable funding		Capital adequacy ratio	
	(1)	(2)	(3)	(4)
LP	0.0464***	0.0460***	0.0342***	0.0341***
	(3.6667)	(3.2847)	(3.5110)	(3.6338)
$SF\_Dep \times LP$	-0.0457***	-0.0404**		
	(-2.6905)	(-2.3896)		
SF_Dep	0.0521***	0.0485**		
	(2.7642)	(2.0476)		
$CAR\_dum \times LP$			-0.0185*	-0.0210*
			(-1.7469)	(-1.6708)
CAR_dum			0.0126	0.0417**
			(0.8159)	(2.2899)
Controls	NO	YES	NO	YES
Bank FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	1,917	1,462	1,887	1,457
Within R^2	0.0197	0.0724	0.0091	0.0689

Notes: The *t*-statistics are reported in the parentheses, and all the control variables are lagged one period. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively. The control variables include the bank size (*BS*), the return on assets (*ROA*), the ratio of noninterest income to total income (*NII*), the capital adequacy ratio (*CAR*), and the ratio of nonperforming loans to total loans (*NPL*).

These results may provide further insights on our mechanisms. First, if the financing cost mechanism had dominated, it would be fairly unlikely to observe a smaller treatment effect in banks with lower initial reliance on stable funding, owing to their impulse to either substantially raise stable funding or significantly reduce total loan volume. However, the portion of bank loan size in total assets did not experience a dramatic decline during the period from 2014 to 2019. In fact, it remained above 42.5% on average and finally reached 51%, given the persistent upward trend starting in 2016. As can be seen from Appendix Figs. B1-1(a) and B1-1(b), it is more likely to be true that such banks were able to obtain abundant low-cost financing in the post-regulation period, benefiting from ample liquidity and an overall continuous decline in money market interest rates. Second, the profit target mechanism may play an important role in determining this effect. That is to say, banks with higher initial levels may prefer to adjust their asset structures (i.e., increase their carbon bias) to meet regulatory requirements while giving priority to profit target because they have limited room to maneuver in liability structure or capital replenishment. This is supported by an insignificant treatment on the bank net interest margin using the flexible estimates analogous to Eq.

(13), as illustrated in Appendix Figs. B1-2(a) and B1-2(b).

6.3 Parallel trend test

Following Nunn and Qian (2011), we first estimate a fully flexible estimating equation (i.e., Eq. (13)) to identify the implementation date before testing the parallel trend. Figs. 3(a) and 3(b) depict the point estimates along with their 95% confidence intervals, considering 2009 and 2013 as the baseline years, respectively. Based on the time-variant interaction term coefficients presented in Fig. 3(a), we can clearly observe a gradual increase in the impact of relative NSFR changes on bank carbon bias after 2014, aligning with our chosen policy date.[15] Moreover, Fig. 3(b) exhibits the consistent pre-parallel trend, with 95% confidence intervals all fluctuating around 0 when $l < 0$. Furthermore, we also observe a general upward trend in coefficients during the post-regulation period, peaking in 2018, with all coefficients being significant at the 5% level except for in 2016.

(a) Implementation date identification

(b) Dynamic effects

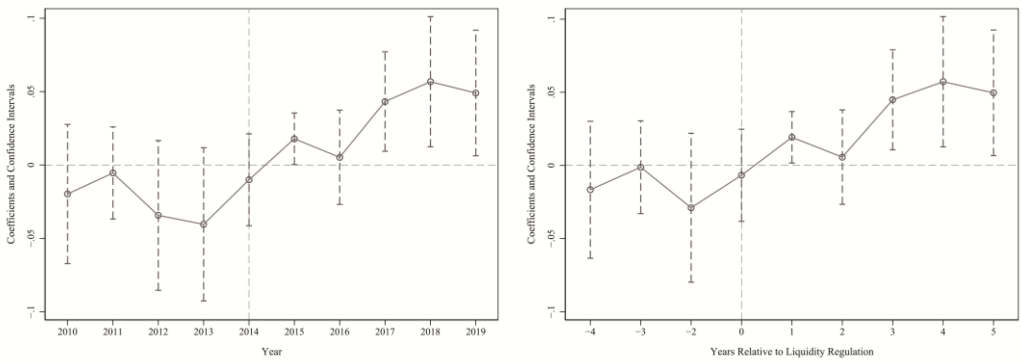

Fig. 3. Parallel trend test of liquidity regulation.

Notes: (a) Flexible estimates of the relationship between liquidity regulation and bank carbon bias based on 2009; (b) flexible estimates of the relationship between liquidity regulation and bank carbon bias based on 2013.

6.4 Robustness checks

6.4.1 Policy exogeneity test

To eliminate the potential concern that banks may anticipate the policy so as to make adjustments in advance (i.e., if they fail to meet the prerequisite of exogenous policy shock), we draw on Li et al. (2023) and exclude the data from the year before implementation. As presented in columns (1)–(2) of Table 5, the coefficients of key explanatory variable LP remain robust, indicating that an apparent policy anticipation effect does not exist.

[15] We also conduct a placebo test to further confirm the absence of pre-trends prior to 2014. Please see Appendix B2 for more details.

6.4.2 Alternative variable

We also try the liquidity ratio as an alternative proxy for liquidity pressure.[16] For consistency with the NSFR, we use liquid liabilities divided by liquidity assets to measure a bank's liquidity ratio, with a higher value meaning lower liquidity pressure. If liquidity regulation indeed increases banks' carbon bias, then the estimated coefficients are expected to be significantly negative. As presented in columns (3)–(4) of Table 5, the coefficients are all negative and statistically significant at the 1% and 10% levels, respectively, leaving our key conclusions unchanged.

6.4.3 Contemporaneous shocks

We consider three main contemporaneous policies: *Deposit Insurance Regulation*, *Guiding Opinions on Regulating the Asset Management Business of Financial Institutions*, and the removal of the LDR limit. Of these policies, we devote special attention to the LDR limit removal due to its potentially strongest impact on banks' liquidity pressure. We extend the baseline model with interaction terms between *LP* and LDR-quartile dummy variables to examine whether banks behave differently under different LDR levels. The coefficients of these interaction terms are of interest, and we expect them to be statistically insignificant. As presented in columns (5)–(6) of Table 5, the coefficients of *LP* remain significant at the 1% level, and as expected, none of the interaction terms are statistically significant, indicating that the treatment effect is unaffected by this removal. Furthermore, the results of the two other shocks and subsample selection based on the LDR limit remain broadly similar to the baseline findings, as detailed in Appendix B3.

Table 5

Robustness checks results.

	Policy anticipation effect		Alternative variable		LDR	
	(1)	(2)	(3)	(4)	(5)	(6)
LP	0.0265***	0.0265***			0.0322***	0.0369***
	(3.3752)	(3.4993)			(2.7830)	(3.8370)
LIQ			-0.0881***	-0.0542*	-0.0002	-0.0058
			(-4.3204)	(-1.9056)	(-0.0208)	(-0.5513)
LDR_LOW					-0.0088	-0.0163
					(-0.6632)	(-1.4177)
LDR_MED					-0.0184	-0.0262
					(-0.9984)	(-1.6226)
LDR_HIGH					0.0322***	0.0369***
					(2.7830)	(3.8370)

[16] We do not use the liquidity match ratio or the high-quality liquidity asset adequacy ratio due to data availability and measurement complexity.

Controls	NO	YES	NO	YES	NO	YES
Bank FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	1,719	1,328	1,846	1,419	1,914	1,462
Within R^2	0.0066	0.0595	0.0006	0.0548	0.0088	0.0666

Notes: This table presents the results considering the policy anticipation effect, an alternative variable, and the loan-to-deposit ratio (*LDR*) limit. Columns (5)–(6) use the interaction regression method, with *LDR_LOW*, *LDR_MED*, and *LDR_HIGH* representing the interaction terms between LP and 2nd, 3rd, and 4th LDR-quartile dummy variables, respectively. The parentheses report *t*-statistics, and all the control variables are lagged one period. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively. The control variables include the bank size (*BS*), the return on assets (*ROA*), the ratio of noninterest income to total income (*NII*), the capital adequacy ratio (*CAR*), and the ratio of nonperforming loans to total loans (*NPL*).

We also conduct other robustness tests by taking instrument variable,[17] shock heterogeneity, and potentially omitted variables into account. Overall, these results all support our primary findings, as detailed in Appendix B3.

6.5 Further discussion

6.5.1 Heterogeneous analysis

Though we can conclude from the baseline results that regulatory-induced liquidity pressure does lead to a significant increase in bank carbon bias, this effect is still in need of further exploration under different dimensions. In fact, banks tend to respond to liquidity regulation by adopting different balance sheet strategies depending on their characteristics and economic environment, thereby ultimately causing differences in carbon bias. Thus, we will analyze the heterogeneous effect across bank type, bank size, and economic environment, respectively.

6.5.1.1 Bank type

We split the full sample into three groups (state-owned with joint-stock, urban, and rural), based on the CBIRC's classification, to examine how the effect varies across distinct bank types. Table 6 shows that there are noticeable differences among the subgroup results. More specifically, the state-owned with joint-stock subsample and urban subsample both have a significantly positive impact on bank carbon bias at the 1% level, with the former having an apparently larger coefficient. However, we observe insignificant effects in the rural subsample. We speculate that state-owned and joint-stock commercial banks, on account of their relatively various sources of funds, are less affected by the regulation. Hence, they are more capable of pursuing short-term profitability while

[17] We use the average liquidity pressure among banks of the same type as the instrument variable for two reasons. First, banks of the same type, with their similar business models, operating scopes, and peer effects, tend to exhibit a strong correlation between the individual and average liquidity pressure. Second, given the way we measure both average liquidity pressure and bank-level carbon bias, it is illogical to expect a direct influence of lower-level carbon bias on higher-level liquidity pressure.

simultaneously meeting regulatory requirements, thus ultimately contributing to an increase in carbon bias. By contrast, urban commercial banks may identify the greater amount of supervision and profitability pressure, that is, the need to strike a balance between short-term profitability and liquidity risk, as the reason for their smaller treatment effect. As for rural commercial banks, they are primarily influenced by the regulation when it comes to increasing the proportion of HQLA (Zhuang and Zhang, 2021), rather than adjusting the loan structure, stemming from their capacity to attract substantial deposits from specific regions.

Table 6

Heterogeneous effects by bank type.

	State-owned with joint-stock commercial banks		Urban commercial banks		Rural commercial banks	
	(1)	(2)	(3)	(4)	(5)	(6)
LP	0.1938** (2.5660)	0.1122*** (3.5910)	0.0314*** (3.0136)	0.0326*** (3.2450)	0.0084 (1.2258)	0.0120 (1.5226)
Controls	NO	YES	NO	YES	NO	YES
Bank FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	179	157	1,021	845	707	453
Within R^2	0.0872	0.4394	0.0102	0.0281	0.0009	0.0914

Notes: The *t*-statistics are reported in the parentheses, and all the control variables are lagged one period. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively. The control variables include the bank size (*BS*), the return on assets (*ROA*), the ratio of noninterest income to total income (*NII*), the capital adequacy ratio (*CAR*), and the ratio of nonperforming loans to total loans (*NPL*).

6.5.1.2 Bank size

A series of liquidity regulations issued after 2014 explicitly document that the main target audience for the LCR and NSFR are commercial banks with assets of no less than ¥200 billion, despite the fact that most banks are covered in practice (Zhang, 2020). In light of this, we divide the full sample into two subgroups with less and no less than ¥200 billion by average total assets and then estimate them respectively. As shown in columns (1)–(4) in Table 7, the treatment effect is significantly positive across the two groups. The coefficient of *LP* is obviously larger in the no-less-than ¥200 billion group, which is in line with the reality of stricter supervision in large banks, though it is only significant at the 10% level. Furthermore, this finding also indirectly reveals the current issue in liquidity regulation for excessive coverage, which brings in additional carbon bias by including banks with assets of less than ¥200 billion in actuality.

6.5.1.3 Economic environment

We further analyze this effect under different economic environments by constructing dummy variables for a macroeconomic cycle, following Zhuang and Zhang (2021). This proceeds in three steps. First, for each bank's headquarter province k in year t, we aggregate its sectoral GVA to obtain the gross domestic product (i.e., $LGDP$) and then calculate the corresponding growth rate (i.e., $LGDPGR_{k,t} = log(LGDP_{k,t} / LGDP_{k,t-1}) \times 100\%$). Second, we separate cyclical components from $LGDPGR_{k,t}$ using the Hodrick-Prescott filter. On this basis, we categorize the economic environment using zero as the threshold, with values above zero indicating upturns and downturns otherwise. Finally, we create two dummies denoted *UP* and *DOWN*, which respectively equal 1 and 0 during upturns and vice versa during downturns. The results are reported in columns (5)–(6) of Table 7. Consistent with the baseline regression, we find that the liquidity regulation has a significantly positive impact on bank carbon bias regardless of economic environment, with a larger effect during upturns. One possible explanation may be related to the typically procyclical pattern of changes in the NSFR within Chinese commercial banks, which primarily lies in the denominator (i.e., RSF) and is reinforced by the loan-dominated asset structure (Pan et al., 2017). During upturns, banks may prefer to pursue short-term profits due to relatively low regulatory-induced liquidity pressure, leading to an increase in carbon bias. Conversely, banks may take caution in increasing carbon bias due to heightened attention on asset-side liquidity risks arising from higher pressure during downturns.

Table 7

Heterogeneous effects by bank size and economic environment.

	Bank size				Economic environment	
	≥ ¥200 bn	≥ ¥200 bn	< ¥200 bn	< ¥200 bn		
	(1)	(2)	(3)	(4)	(5)	(6)
LP	0.0712** (2.4867)	0.0398* (1.7882)	0.0167** (2.5456)	0.0191*** (2.7699)		
$LP \times UP$					0.0327*** (3.0824)	0.0353*** (3.5288)
$LP \times DOWN$					0.0238*** (3.4042)	0.0220*** (3.2078)
Controls	NO	YES	NO	YES	NO	YES
Bank FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	499	460	1,255	986	1,917	1,462
Within R^2	0.0165	0.1681	0.0049	0.0218	0.0074	0.0643

Notes: The *t*-statistics are reported in the parentheses, and all the control variables are lagged one period. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively. The control variables include the bank size

(*BS*), the return on assets (*ROA*), the ratio of noninterest income to total income (*NII*), the capital adequacy ratio (*CAR*), and the ratio of nonperforming loans to total loans (*NPL*).

6.5.2 Bank proactive liquidity management

It is worth noting that a potential competing explanation for our findings is that the pre-post differences in the NSFR may arise from bank proactive liquidity management. To investigate this possibility, we first measure the target NSFR for each bank and then reestimate our baseline model in two ways to remove such interference, with the target included or grouped by the median of the target NSFR. If we could obtain a significant coefficient for LP after controlling for the target NSFR, or an insignificant coefficient difference across two subgroups (i.e., the low- and high-target NSFR groups), we can infer that the baseline results capture liquidity pressure from the regulation, rather than proactive liquidity management.

We evaluate the target NSFR based on bank-specific characteristics and their dynamic adjustment behaviors, referring to DeYoung and Jang (2016),[18] as shown in column (1) of Table 8. The average estimated target NSFR is 1.22, which is fairly close to the average value of 1.29 in our raw data, suggesting that banks do actively manage their liquidity positions by setting target NSFRs. We can see from column (2) that the coefficient of LP remains significant even after controlling for the target NSFR, while the target itself is insignificant. The results of the two subgroups are displayed in columns (3)–(4). The coefficients of LP are positive in both the low- and high-target NSFR groups, and they are significant at the 1% and 10% levels, respectively. Meanwhile, the coefficient difference is insignificant with a p-value of 0.488, accepting the null hypothesis of Fisher's Permutation test. In sum, our baseline conclusions remain robust after considering a possible competing explanation; that is, they cannot be fully explained by banks' proactive liquidity management.

Table 8

Target NSFR estimate results.

	$NSFR_{i,t}$	Directly control	Low-target NSFR	High-target NSFR
	(1)	(2)	(3)	(4)
$NSFR_{i,t-1}$	0.7433*** (3.4415)			
LP		0.0281*** (3.7012)	0.0241*** (3.1364)	0.0251* (1.8075)
$NSFR\_Target$		0.0959 (0.7805)		

[18] Following DeYoung and Yang (2016) and Pan et al. (2016, 2017), we select the ratio of equity to assets, the dummy for publicly traded commercial banks, the ratio of credit commitments to assets, the ratio of mortgage loans to total loans, the natural log of average total assets, the return on assets, the ratio of noninterest income to total income, the capital adequacy ratio, and the ratio of nonperforming loans to total loans as bank-specific characteristics. Full details on the measurement are provided in Appendix B4.

Controls	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Mean target NSFR	1.2181			
Mean estimated NSFR	1.2920			
Adjustment speed	0.2567			
Observations	1,465	1,462	709	706
Number of IV	26			
AR(1)	-3.9508 (0.0001)			
AR(2)	1.2478 (0.2121)			
Hansen	6.9335 (0.3270)			
Within R^2		0.0649	0.0235	0.0842
Empirical P			-0.0010 （0.4880）	

Notes: The parentheses report *z*-statistics in column (1) and *t*-statistics in columns (2)–(4). All the control variables are lagged one period. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively. AR(1) and AR(2) represent the results of an Arellano-Bond test for first- and second-order serial correlation of the errors. "Hansen" represents the Hansen test value and the corresponding *p*-value under a system GMM. Columns (3)–(4) are grouped by the median of the target NSFR, and the empirical *p*-value is used to test the coefficient difference in LP between groups. It is obtained by extracting 1,000 times through bootstrapping, with the null hypothesis being that there is no difference between groups.

7. Conclusions and policy implications

This study theoretically demonstrated the mechanisms of liquidity regulation on bank carbon bias and empirically tested them using Chinese commercial bank data.[19] First, we outlined a simplified balance sheet model to illustrate the underlying mechanisms of the treatment effect, with results indicating that the tighter liquidity requirement leads to increased bank carbon bias through two channels, namely, reducing asset profitability and increasing financing costs. Then we employed a continuous differences-in-differences approach to test and quantify the impact of liquidity regulation on bank carbon bias using a dataset of 213 commercial banks during the period 2009–2019. Our empirical evidence showing a significantly positive treatment effect suggests that when facing higher liquidity pressure, the aggregated carbon bias of sample banks increases 23% after the implementation in comparison to before the implementation. More specifically, we can identify the slow pace of bank loan decarbonization, rather than the slow promotion of low-carbon development, as the reason for this increase. These findings were generally confirmed by a series of robustness checks. Subsequently, the moderating effect reveals the considerable sensitivity of our

[19] It should be noted that caution is warranted when applying our conclusions and policy implications because the empirical analysis is limited to the long-term regulatory indicator NSFR.

results to the initial conditions, that is, demonstrating a smaller impact when banks have lower initial reliance on stable funding or the capital adequacy ratio. This would seem to provide support for the crucial role of the profit target mechanism in increasing bank carbon bias. Finally, we explored further heterogeneity in treatment effects across bank type, bank size, and economic environment. We find that this effect is mainly present in state-owned, joint-stock, and urban commercial banks and that it is more pronounced during economic upturns and for banks with assets of no less than ¥200 billion, than during economic downturns and for banks with assets of less than ¥200 billion. Furthermore, we rule out the potential competing explanation on the ground that our baseline results remain robust after considering bank proactive liquidity management.

Our findings have two policy implications. First, given that the current liquidity regulatory framework may impede the green transition of the Chinese banking sector and fail to fully leverage banks' potential role in greening the economy, authorities should be keenly aware of its potential pitfalls. Second, we propose three solutions to address bank carbon bias: (1) Integrate carbon bias from liquidity regulation into the macro-prudential assessment framework to increase the cost for banks engaging in such behavior. (2) Offer additional subsidies under the green finance framework. (3) Adjust regulatory parameters to ease banks' liquidity pressure while ensuring their safety and soundness.

Appendix A1.

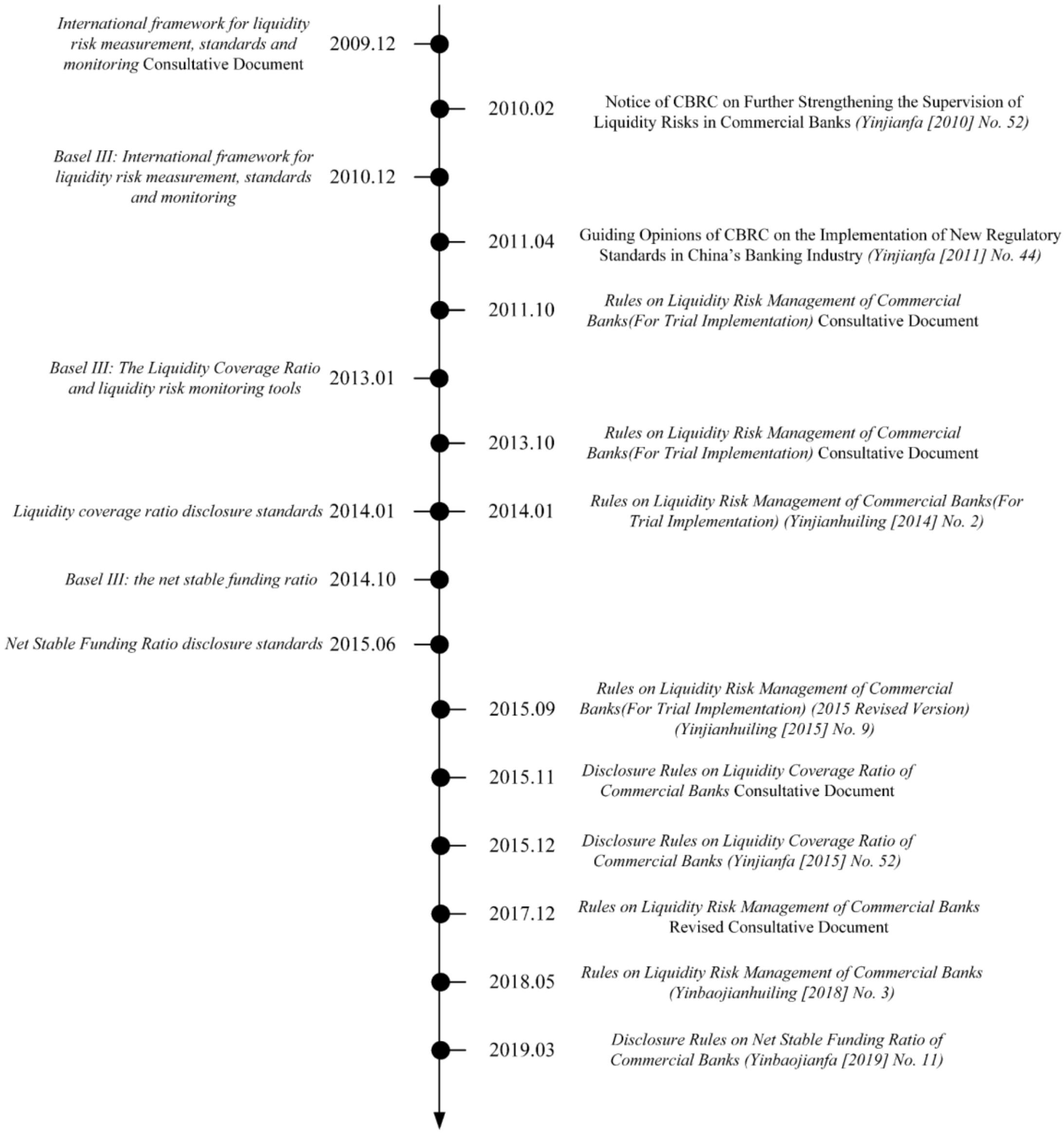

Fig. A1. A chronology of key events in the evolution of liquidity regulations from the BCBS and in China.
Notes: The left side of the timeline presents the key events in the evolution of liquidity regulations from the BCBS, while the right side presents the evolution process for commercial banks in China.

Appendix A2.

Table A2

The correspondence between CEADs and GB/T 4754-2017.

Economic activities (CEADs)	Industrial classification for national economic activities (GB/T 4754-2017)	
	Subcategory	Parent category
Farming, forestry, animal husbandry, fishery and water conservancy	\	Agricultural forestry, animal husbandry and fishery
Logging and transport of wood and bamboo	Logging and transport of timber and bamboo	
Coal mining and dressing	Coal mining and dressing	Mining
Petroleum and natural gas extraction	Petroleum and natural gas extraction	
Ferrous metals mining and dressing	Ferrous metals mining and dressing	
Nonferrous metals mining and dressing	Nonferrous metals mining and dressing	
Nonmetal minerals mining and dressing	Nonmetal minerals mining and dressing	
Other minerals mining and dressing	Other minerals mining and dressing	
Food processing	Processing of food from agricultural products	Manufacturing
Food production	Food manufacturing	
Beverage production	Alcohol, beverages, and refined tea manufacturing	
Tobacco processing	Tobacco manufacturing	
Textile industry	Textiles manufacturing	
Garments and other fiber products	Textiles manufacturing and apparel industry	
Leather, furs, down and related products	Leather, fur, feather and related products manufacturing and footwear industry	
Timber processing, bamboo, cane, palm fiber and straw products	Timber processing; wood, bamboo, rattan, palm, and straw products manufacturing	
Furniture manufacturing	Furniture manufacturing	
Papermaking and paper products	Paper and paper products manufacturing	
Printing and record medium reproduction	Printing and recorded media	
Cultural, educational and sports articles	Articles for culture, education, art, sports, and entertainment manufacturing	

(continued)

Economic activities (CEADs)	Industrial classification for national economic activities (GB/T 4754-2017)	
	Subcategory	Parent category
Petroleum processing and coking	Petroleum processing, coking, and nuclear fuel processing	
Raw chemical materials and chemical products	Chemical raw materials and chemical products manufacturing	
Medical and pharmaceutical products	Medicines manufacturing	
Chemical fiber	Chemical fibers manufacturing	
Rubber products	Rubber and plastics manufacturing	
Plastic products	Rubber and plastics manufacturing	
Nonmetal mineral products	Non-metallic mineral products manufacturing	
Smelting and pressing of ferrous metals	Smelting and processing of ferrous metals	
Smelting and pressing of nonferrous metals	Smelting and processing of nonferrous metals	
Metal products	Metal products manufacturing	
Ordinary machinery	General purpose machinery manufacturing	
Equipment for special purposes	Special purpose machinery manufacturing	
Transportation equipment	Railway, ships, aerospace and other transportation equipment	
Electric equipment and machinery	Electrical machinery and equipment manufacturing	
Electronic and telecommunications equipment	Computers, communication and other electronic equipment manufacturing	
Instruments, meters, cultural and office machinery	Measuring instruments manufacturing	
Other manufacturing industry	Other manufacturing	
Scrap and waste	Comprehensive use of waste resources	
Production and supply of electric power, steam and hot water	\	Production and supply of electricity, heat, gas and water
Production and supply of gas	Production and distribution of gas	
Production and supply of tap water	Production and distribution of gas	
Construction	\	Construction
Wholesale, retail trade and catering services	\	Wholesale and retail trades
Transportation, storage, post and telecommunication services	\	Transportation, storage and post
Others	\	\
Urban	\	\
Rural	\	\

Appendix A3

Table A3

The on- and off-balance sheet items and the corresponding weights used to calculate NSFR.

Required stable funding (RSF)		Available stable funding (ASF)	
On-balance sheet			
Assets	Weights (%)	Liabilities and equity	Weights (%)
1. Total earning assets		**1. Deposits and short-term funding**	
1.1 Loans		1.1 Deposits and short-term funding	
1.1.1 Mortgage loans	65	1.1.1 Demand deposit	90
1.1.2 Other loans	85	1.1.2 Term deposit	95
1.2 Other earning assets		1.2 Deposits from banks and other financial institutions	0
1.2.1 Lendings to banks and other financial institutions	50	1.3 Other deposits and short-term borrowings	0
1.2.2 Financial investments	50	**2. Other interest-bearing liabilities**	
1.2.2.1 Financial assets measured at amortized cost		2.1 Long-term financing (Bond payable)	100
1.2.2.2 Financial investments measured at FVTPL		**3. Other noninterest-bearing liabilities**	0
1.2.2.3 Financial investments measured at FVTOCI		**4. Other reserves**	100
2. Fixed assets	100	4.1 Required reserve	
3. Nonearning assets		4.2 Excessive reserve	
3.1 Cash and due from banks	0	4.3 Foreign currency reserve	
3.3 Goodwill	100	**5. Equity**	100
3.4 Intangible assets	100		
3.5 Other assets	100		
Off-balance sheet			
Credit commitment	5		

Notes: In 2017, the Ministry of Finance of the People's Republic of China announced the new classification of financial instruments, that is, *Accounting Standards for Business Enterprises No. 22—Recognition and Measurement of Financial Instruments (CAS22) (Caihui [2017] No. 7)*. We have taken this into account by calculating the financial investments under different criteria based on the annual report.

Appendix A4

Table A4

The sample coverage for the entire banking sector in China in terms of total assets by year.

Year	No. of banks	Total assets of sample banks (bn)	Total assets of banking sector (bn)	Portion (%)
2009	93	53,641.78	60,164.00	89.16%
2010	119	64,504.65	72,417.60	89.07%
2011	140	77,535.60	86,250.20	89.90%
2012	177	93,706.64	102,189.20	91.70%
2013	198	108,309.70	116,236.20	93.18%
2014	205	128,163.04	132,005.70	97.09%
2015	208	145,434.12	153,065.40	95.01%
2016	212	167,136.22	178,577.20	93.59%
2017	199	177,240.02	193,201.50	91.74%
2018	191	183,360.85	205,981.10	89.02%
2019	175	202,394.96	235,090.50	86.09%
Mean	174	127,402.51	139,561.69	91.41%

Notes: Column (2) reports the number of banks observed each year in our sample. Columns (3)–(4) respectively present the total assets of sample banks and the entire Chinese banking sector, with the latter collected from the *Almanac of China's Finance and Banking*. To improve calculation precision, we include only state-owned commercial banks, joint-stock commercial banks, urban commercial banks, and rural commercial banks when calculating total banking sector assets, aligning with the bank types in our sample. Accordingly, we use each bank's average end-of-period asset balance between the current and last years to calculate total sample banks' assets for consistency with the main text. Column (5) shows the sample coverage of total banking sector assets obtained from dividing column (3) by column (4).

Appendix A5.

Table A5

The median of total carbon emissions and classification of high-carbon sectors during 2009–2014.

Year	Median (Mt)	High-carbon sectors
2009	186.73	Manufacturing; production and supply of electricity, heat, gas and water; and transportation, storage and post
2010	206.622	Manufacturing; production and supply of electricity, heat, gas and water; and transportation, storage and post
2011	201.472	Manufacturing; production and supply of electricity, heat, gas and water; and transportation, storage and post
2012	209.022	Manufacturing; production and supply of electricity, heat, gas and water; and transportation, storage and post
2013	221.678	Manufacturing; production and supply of electricity, heat, gas and water; and transportation, storage and post
2014	157.566	Manufacturing; production and supply of electricity, heat, gas and water; and transportation, storage and post
2015	146.209	Mining; manufacturing; and transportation, storage and post
2016	127.791	Mining; manufacturing; production and supply of electricity, heat, gas and water; and transportation, storage and post
2017	133.393	Manufacturing; production and supply of electricity, heat, gas and water; and transportation, storage and post
2018	125.641	Manufacturing; production and supply of electricity, heat, gas and water; and transportation, storage and post
2019	122.16	Mining; manufacturing; production and supply of electricity, heat, gas and water; and transportation, storage and post

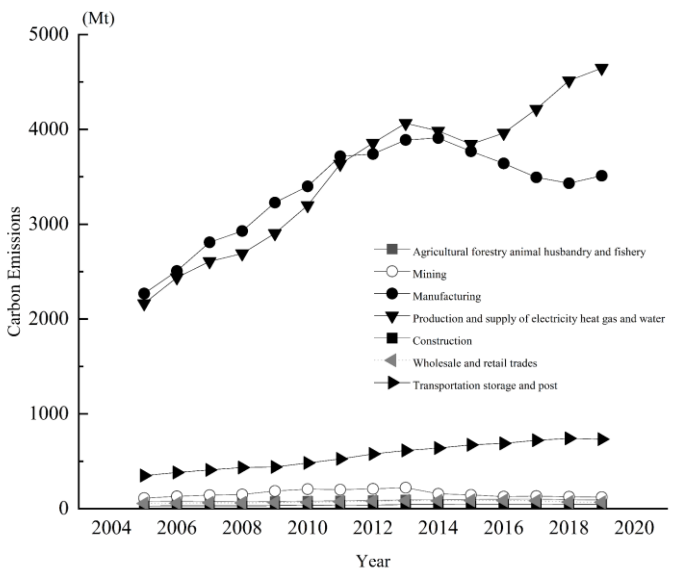

Fig. A5. Sectoral total carbon emissions during 2009–2019.

Appendix B1

Table B1 reports the mean and median values of the portion of bank loan size in total assets from 2014 to 2019. There was no significant decline during this period, and indeed, it remained above 42.5% on average. Meanwhile, it has even started to increase since 2016, with mean values reaching 43.9%, 47.9%, and 51.0% in 2017, 2018, and 2019, respectively.

Table B1

The portion of bank loan size in total assets from 2014 to 2019.

Year	Mean	Median
2009	50.87	51.10
2010	47.22	47.38
2011	46.92	49.42
2012	46.53	47.84
2013	45.69	47.28
2014	46.64	47.39
2015	44.63	45.19
2016	42.55	42.47
2017	43.90	43.70
2018	47.92	48.09
2019	50.95	51.03

Notes: The portion of bank loan size in total assets is winsorized at the 1% and 99% levels.

Figs. B1-1(a) and B1-1(b) plot the portion of interest cost to money market interest rates during the periods 2005–2019 and 2009–2019, respectively. We choose four common indicators to proxy for money market interest rates, that is, DIBO007, DR007, R007, and Shibor007. As we can observe, money market interest rates exhibited an overall downward trend from 2014 to 2019. This implies that in spite of an upward trend in the interest cost since 2016, banks did not experience a sharp increase in financing costs during the post-regulation period.

(a) 2009–2019

(b) 2014–2019

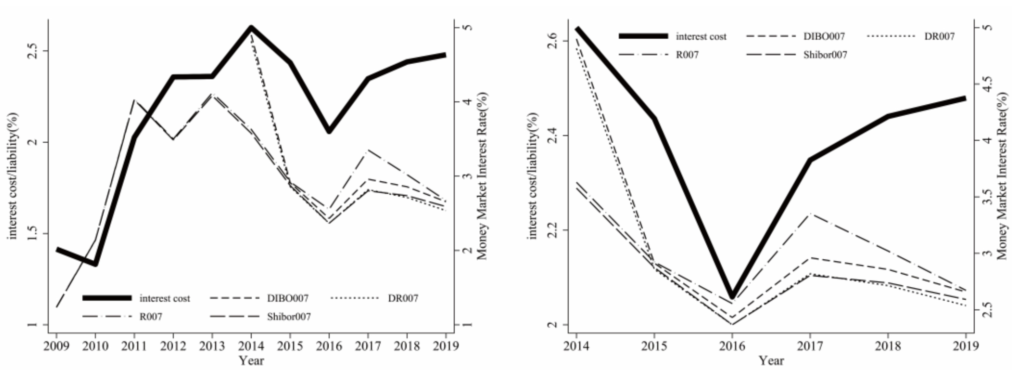

Fig. B1-1. The portion of interest cost to money market interest rates.

[Figs. B1-2(a)](#) and [B1-2(b)](#) show the flexible estimates of the relationship between liquidity regulation and bank net interest margin, considering 2009 and 2013 as the baseline years, respectively. We do not find a significant treatment effect in this case, with the 95% confidence intervals all fluctuating around 0 when $l > 0$ (i.e., after 2014).

(a) Based on 2009 (b) Based on 2013

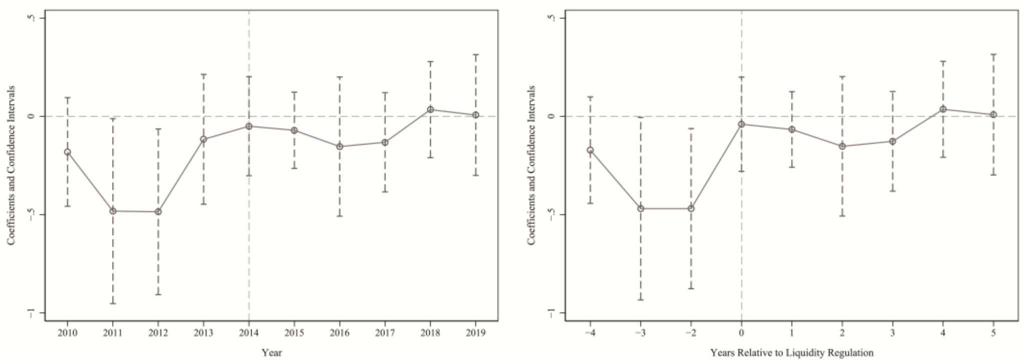

Fig. B1-2. Flexible estimates of the relationship between liquidity regulation and bank net interest margin.

Appendix B2.

To further test the parallel assumption, we extend the baseline model with interaction terms between liquidity pressure and year dummies prior to the chosen policy implementation date (i.e., 2010–2013, excluding 2009 to avoid simultaneity). This specification enables us to examine the difference in liquidity pressure among sample banks prior to the liquidity regulation. If our chosen year is appropriate, these interaction terms are expected to be statistically insignificant. The results are reported in Table B2. As we can see, none of the interaction terms are statistically significant regardless of adding individually or jointly. Moreover, the *F*-test for the joint significance of all interaction terms yields a *p*-value of 0.4735, implying that the sum of the coefficients is equal to zero. Therefore, the rationale for our chosen policy implementation year is further confirmed since there were no significant differences in bank carbon bias prior to 2014. In other words, our analysis satisfies the key identifying assumption.

Table B2

Placebo test.

	(1)	(2)	(3)	(4)	(5)
LP	0.0275*** (3.6537)	0.0278*** (3.6891)	0.0272*** (3.6090)	0.0267*** (3.5990)	0.0256*** (3.4699)
$NSFR \times 2010$	-0.0135 (-0.6026)				-0.0179 (-0.7598)

	(1)	(2)	(3)	(4)	(5)
NSFR×2011		0.0054 (0.3661)			-0.0029 (-0.1816)
NSFR×2012			-0.0263 (-1.0465)		-0.0321 (-1.2684)
NSFR×2013				-0.0325 (-1.2350)	-0.0375 (-1.4067)
Controls	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	1,462	1,462	1,462	1,462	1,462
Within R^2	0.0628	0.0625	0.0636	0.0643	0.0664
F test					0.8854 (0.4735)

Notes: This table presents the results of the placebo test, where the baseline model is extended with interaction terms between liquidity pressure and year dummies prior to 2014, excluding 2009. The first four columns present results with individual interaction terms, while the final column includes all interaction terms jointly. The bottom row presents an *F*-test for the joint significance of all the interaction terms, with the null hypothesis being no significant differences in bank carbon bias prior to 2014. The *t*-statistics are reported in the parentheses, and all the control variables are lagged one period. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively. The control variables include the bank size (*BS*), the return on assets (*ROA*), the ratio of noninterest income to total income (*NII*), the capital adequacy ratio (*CAR*), and the ratio of nonperforming loans to total loans (*NPL*).

Appendix B3.

B3.1 Instrumental variable (IV) estimation

We use the average bank liquidity pressure of the same type over the year (*LP_average*) as the instrument. Banks of the same type not only share similar business models and scopes but also have the peer effect in terms of liquidity risk management. Therefore, it is reasonable to expect that the liquidity pressure experienced by individual banks is highly correlated with the average liquidity pressure observed among banks of the same type. Meanwhile, owing to different hierarchical positions, the group-level average liquidity pressure may not affect the individual-level bank carbon bias directly and vice versa. In fact, the average liquidity pressure is more likely to influence bank carbon bias exclusively through its effect on each bank's contemporaneous liquidity pressure. Overall, the preliminary analysis suggests that our instrumental variable is generally reasonable in satisfying the requirements of correlation, exogeneity, and exclusivity.

The results of the IV regressions are reported in Table B3-1. We can observe from column (1) that in the first stage of our two-stage least squares estimations, the average bank liquidity pressure of the same type is significantly positive related to each bank's contemporaneous liquidity pressure at the 1% level. The corresponding *F*-value equals 32.49, which is greater than 10, thus further validating the strength and relevance of the selected instrumental variable. As shown in column (2), the average bank liquidity pressure of the same type is positive and significant at the 5% level in the second stage, which is broadly consistent with our main findings.

B3.2 Controlling for shock heterogeneity

We extend our baseline model by including the interaction fixed effect $banktype \times year$ to control for heterogeneity in shock. As presented in columns (3)–(4) of Table B3-1, the liquidity pressure remains significantly positive at the 1% level, supporting our baseline results.

B3.3 Potentially omitted variables

We have controlled for bank and year fixed effects in the baseline model, which can substantially alleviate omitted variable bias in static panel data. Even so, there remains a possibility of overlooking unobservable variables correlated with the key regressor, which may then result in inconsistent estimates. To address this concern, we reestimate the baseline model with 1-year lagged bank carbon bias (i.e., $CB_{j,t-1}$) based on a system generalized method of moments (GMM) estimation, referring to Ding andand Wu (2023). As reported in columns (5)–(6) of Table B3-1, the Arellano-Bond test for error autocorrelation and Hansen test for overidentifying restrictions uniformly support the validity of our dynamic panel model. The coefficients of $CB_{j,t-1}$ are both significantly positive at the 1% level regardless of the control variables, thus implying an evident momentum effect in bank carbon bias. After introducing this dynamic feature, the coefficients of LP are still significantly positive at the 5% or 10% level, which is consistent with our main results.

Table B3-1

IV estimation and shock heterogeneity.

	IV estimation		Shock heterogeneity		Potentially omitted variables	
	(1)	(2)	(3)	(4)	(5)	(6)
LP		0.1811** (2.1564)	0.0232*** (3.5019)	0.0262*** (3.7806)	0.0111* (1.6653)	0.0158** (2.4566)
LP_average	0.8960*** (5.6998)					
L.CB					1.0030*** (11.1456)	0.8811*** (9.4594)
Controls	YES	YES	NO	YES	NO	YES
Bank FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES			YES	YES
Bank type × year FE			YES	YES		
Observations	1,462	1,462	1,907	1,455	1,705	1,465
Within R^2			0.0056	0.0245		
F-value	32.49 （0.000）					
No. of IV					25	30
AR(1)					-2.2447 (0.0248)	-1.9733 (0.0485)

AR(2)		1.4960 (0.1347)	1.3625 (0.1730)
Hansen		18.5912 (0.1363)	18.0189 (0.1568)

Notes: This table presents the results of the IV regression, shock heterogeneity, and the GMM estimation. The parentheses report *t*-statistics in columns (1)–(4) and *z*-statistics in columns (5)–(6). AR(1) and AR(2) represent the results of the Arellano-Bond test for first- and second-order serial correlation of the errors. "Hansen" represents the Hansen test value and the corresponding *P*-value under a system GMM. All the control variables are lagged one period. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively. The control variables include the bank size (*BS*), the return on assets (*ROA*), the ratio of noninterest income to total income (*NII*), the capital adequacy ratio (*CAR*), and the ratio of nonperforming loans to total loans (*NPL*).

B3.4 Other contemporaneous shocks

The first contemporaneous event is the enforcement of *Deposit Insurance Regulation (Guowuyuanling [2015] No. 660)* in 2015, henceforth referred to as the "DIR." It has greatly influenced liquidity risk and thus may in turn drive our identification and estimation of the treatment effect. To exclude this interference, we endeavor to seek a pure subsample (i.e., one nearly uncontaminated by the DIR). Wang et al. (2018) find that the DIR did not significantly impact large state-owned and joint-stock banks because the policy has merely made implicit government guarantees explicit while the "too big to fail" belief is still well accepted. Consequently, we select a subsample of banks that are ranked in the top 15 of total deposit size on an annual basis.[20] As we can see from columns (1)–(2) of Table B3-2, the treatment effect remains significantly positive after considering the DIR.

The second contemporaneous item concerns *Guiding Opinions on Regulating the Asset Management Business of Financial Institutions (Yinfa [2018] No. 106)*, henceforth referred to as the "AMBFI." It was jointly released by four official agencies (i.e., the People's Bank of China, CBRC, China Securities Regulatory Commission, and State Administration of Foreign Exchange) on April 27, 2018. Considering that this policy might come into conflict with the effect of liquidity regulation, we reestimate our baseline model after excluding the samples from 2018 onward, as presented in columns (3)–(4) of Table B3-2. We find that the treatment effect remains significant and positive at the 1% level, suggesting the robustness of our primary findings.

The last consideration concerns the 2015 removal of the 75% LDR limit, which had up until then been a key liquidity regulatory ratio in China for decades. It is natural to conjecture that this shift may have profound implications for banks' liquidity and therefore may introduce a bias in our estimation. To net out this influencing factor, we reestimate the baseline model by only including

[20] The subsample generally overlaps with state-owned and joint-stock banks but also includes the Bank of Beijing and Bank of Shanghai while excluding Hengfeng Bank, CZBank, and China Bohai Bank.

banks with LDRs equal to or below 75% throughout the whole sample period. Our rationale for this selection is that banks consistently within the LDR limit are virtually unaffected by this removal. As presented in columns (5)–(6) of Table B3-2, the effect remains significantly positive at the 1% level, which is consistent with our main findings.

Table B3-2

Other contemporaneous shocks.

	DIR		AMBFI		LDR	
	(1)	(2)	(3)	(4)	(5)	(6)
LP	0.2044** (2.7610)	0.1075** (2.8934)	0.0227*** (2.9366)	0.0222*** (2.8507)	0.0317*** (3.7129)	0.0337*** (4.0371)
Controls	NO	YES	NO	YES	NO	YES
Bank FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	164	143	1,551	1,128	1,678	1,267
Within R^2	0.0978	0.4996	0.0050	0.0369	0.0098	0.0635

Notes: This table presents the results considering three contemporaneous shocks, the DIR, AMBFI and LDR, in columns (1)–(2), (3)–(4), and (5)–(6), respectively. Columns (5)–(6) use the subsample selection method by only including banks with LDRs equal to or below 75% throughout the whole sample period. The *t*-statistics are reported in the parentheses, and all the control variables are lagged one period. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively. The control variables include the bank size (*BS*), the return on assets (*ROA*), the ratio of noninterest income to total income (*NII*), the capital adequacy ratio (*CAR*), and the ratio of nonperforming loans to total loans (*NPL*).

Appendix B4.

Our measurement proceeds in three steps. First, we construct a decision function based on the assumption that all banks have target NSFRs determined by their characteristics, as follows:

$$NSFR^*_{j,t} = \beta_{j,t-1} X_{j,t-1}, \tag{B4.1}$$

where $NSFR^*_{j,t}$ represents the target value of bank j in year t and $X_{j,t-1}$ represents the nine bank-specific characteristics, including the ratio of equity to assets, the dummy for publicly traded commercial banks, the ratio of credit commitments to assets, the ratio of mortgage loans to total loans, the natural log of average total assets, the return on assets, the ratio of noninterest income to total income, the capital adequacy ratio, and the ratio of nonperforming loans to total loans. $\beta_{j,t-1}$ represents a vector of coefficients to be estimated. Note that if $\beta \neq 0$, then there do exist target NSFRs within banks.

Second, we investigate the dynamic adjustment behaviors of banks in response to shocks. Exogenous shocks can push banks away from their target NSFRs. Should this occur, potentially costly and time-consuming adjustments would be almost inevitable for banks to return to their desired values. We take this process into account by formulating a hypothesis on the adjustment speed, as follows:

$$NSFR_{j,t} - NSFR_{j,t-1} = \lambda\left(NSFR^{*}_{j,t} - NSFR_{j,t-1}\right) + \varepsilon_{j,t}, \tag{B4.2}$$

where λ, $\varepsilon_{j,t}$, $NSFR_{j,t}$, and $NSFR_{j,t-1}$ refer to the adjustment speed toward the target NSFR, the error term, and the estimated NSFR of bank j in years t and $t-1$, respectively. Note that the larger the value of λ, the lower the adjustment cost that banks would bear.

Third, we associate the estimated NSFR with the target NSFR. After substituting Eq. (B4.1) into Eq. (B4.2), we rearrange to arrive at the following equation:

$$NSFR_{j,t} = \lambda\beta_{j,t-1}X_{j,t-1} + \left(1-\lambda\right)NSFR_{j,t-1} + \varepsilon_{j,t}. \tag{B4.3}$$

We can recover λ from the estimated parameter $\left(1-\lambda\right)$, then calculate β by dividing the estimated parameter $\lambda\beta$ by λ and finally substitute β back into Eq. (B4.1) to obtain $NSFR^{*}_{j,t}$.

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