The British Accounting Review xxx (xxxx) xxx

Contents lists available at ScienceDirect

The British Accounting Review

journal homepage: www.elsevier.com/locate/bar

FinTech adoption in banks and their liquidity creation

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A R T I C L E I N F O

Keywords:
Bank liquidity creation
FinTech
COVID-19
Bank risk
California consumer privacy Act (CCPA)

A B S T R A C T

Utilizing an innovative financial technology (FinTech) index based on media sources, we analyse the effects of FinTech adoption on bank liquidity creation for a sample of the top 300 United States banks from Q1 2015 to Q2 2021. Our findings reveal a consistent negative association between FinTech adoption and bank liquidity creation, even during the coronavirus disease (COVID-19) pandemic. This relationship remains robust after conducting multiple rigorous tests including propensity score matching and difference-in-differences tests to address endogeneity problems. Overall, these results underscore the transformative influence of FinTech on fundamental liquidity creation function within traditional banking.

1. Introduction

Innovation in financial technology (FinTech) leads to the increased efficiency of financial markets in delivering financial services to the public in this age of digitalisation (Thakor, 2020). Over the past few decades, the tremendous growth of FinTech has played a critical role in financial markets in terms of information transmission and financial intermediation (Chen, 2016; Goldstein et al., 2019; Haddad & Hornuf, 2019). FinTech typically refers to the emerging technologies that improve the information transmission, risk management framework and quality of data processing of financial institutions (Gai et al., 2018; Goldstein et al., 2019; Thakor, 2020). FinTech applications are widely adopted by financial institutions for various operational and managerial aspects. For instance, technologies related to payments, clearing and settlement services (e.g., peer-to-peer [P2P] lending, crowdfunding platforms and online banking) and market support services (e.g., data processing and risk management applications) constitute more than half of the existing FinTech applications (Basel Committee on Banking Supervision [BCBS], 2018).

In line with contemporary financial intermediation theory, banks play a central role in fostering liquidity within the economy. They achieve this by catering to two primary groups of clients: borrowers and depositors. Traditionally, banks create liquidity by financing relatively long-term illiquid assets (e.g., business loans) with relatively short-term liquid liability (e.g., deposits) (Bryant, 1980; Diamond & Dybvig, 1983). They can also create liquidity through off-balance sheet activities, such as offering standby letters of credit and loan commitments to their customers (Kashyap et al., 2002; Thakor, 2005). Thus, FinTech adoption in banking has changed the way banks conduct their business—that is, from offline (e.g., branches) to online services, which has improved banks' operating efficiency and service quality (Gai et al., 2018; Lee et al., 2021). Certain studies have suggested that online services and other FinTech applications enhance banks' financial inclusion, which enables them to conduct more business by improving users' accessibility to their services (Acharya et al., 2008; Chen, 2016; Maskara et al., 2021; Senyo & Osabutey, 2020). Further, FinTech adoption by banks increases their performance, stability and efficiency and decreases credit risk (Cheng & Qu, 2020; Deng et al., 2021; Wang et al., 2020,

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https://doi.org/10.1016/j.bar.2024.101322
Received 31 December 2022; Received in revised form 11 December 2023; Accepted 9 January 2024
Available online 11 January 2024
0890-8389/

2021). Although many studies have investigated the relationship between banks' FinTech adoption and their performance in the Chinese market (Cheng & Qu, 2020; Wang et al., 2020, 2021, 2023), little is known about whether, how and to what extent such adoption affects banks' liquidity creation in the United States (US) market. The minimal attention to the impact of FinTech adoption on bank liquidity creation is unfortunate, because creating liquidity in the economy is regarded as a major function of banks. Thus, our goal is to address this gap in the literature through the present study.

The coronavirus disease (COVID-19) pandemic not only negatively affected bank stock prices (Demirgüç-Kunt et al., 2021) but has also reduced bank lending and consumer spending (Andersen et al., 2022; Çolak & Öztekin, 2021). Typically, banks reduce their liquidity creation during a financial recession by decreasing credit lending to mitigate their risk exposure (Acharya et al., 2018; Nguyen et al., 2020). However, banks actively adopted FinTech (e.g., internet-based technology) during the COVID-19 pandemic period to continue sharing work-related information with employees who worked remotely, thus ensuring that their businesses continued to function (Tønnessen et al., 2021). Banks that had advanced FinTech adoption remained operational during this pandemic period; thus, they were able to optimise their loan portfolio by using advanced business analysis models and algorithms during the various lockdown periods. Therefore, we aim to address the unexplored issue of the effect of the COVID-19 pandemic on the relationship between FinTech adoption and bank liquidity creation.

Our sample consists of the top 300 bank holding companies (BHCs) in the US from the first quarter of 2015 (Q1 2015) to the second quarter of 2021 (Q2 2021). We construct FinTech indexes to measure banks' FinTech adoption by using a news count of banks and their FinTech adoption. After controlling for potential liquidity creation determinants and bank fixed effects and year-quarter fixed effects, we find that banks that have high levels of FinTech adoption create less total, on-balance sheet and asset-side liquidity. Our finding for the negative association between FinTech adoption and bank liquidity creation continued to hold throughout the COVID-19 pandemic period. We also evaluate the effect of various FinTech types on banks' liquidity creation. The findings suggest that the adoption of cloud and internet are dominant in reducing banks' liquidity creation. Furthermore, we find that banks create less liquidity when adopting artificial intelligence (AI), blockchain and internet-based FinTech during this pandemic period.

We conduct some robustness checks and endogeneity tests and find that the results of this study hold. For instance, we use propensity score matching (PSM) and a system generalised method of moments (GMM) model to mitigate endogeneity issues. Further, we select the California Consumer Privacy Act (CCPA) as the event in a difference-in-differences (DiD) model to address endogeneity issues with the parallel trends test and a placebo check as a robustness check. The CCPA reduces the data analysis ability of firms, including banks, by limiting their accessibility to their customers' personal information. Furthermore, we measure banks' FinTech adoption using alternative independent variables, including the ratio of individual banks' total FinTech news to the bank's total news for each quarter. The results of this analysis are consistent with our baseline results.

Our study makes several noteworthy contributions to the existing literature. First, we augment the growing body of research on liquidity creation examining the influence of bank-level factors and government intervention or regulation on this phenomenon (Díaz & Huang, 2017; Huang et al., 2018; Jiang et al., 2019; Zheng et al., 2019). In this context, our study adds to the knowledge by establishing that the adoption of FinTech by banks plays a pivotal role in shaping liquidity creation. Furthermore, we diverge from the findings of Guo and Zhang's (2023) study, which observed a positive correlation between banks' FinTech adoption and their liquidity creation using data from 97 banks in the Chinese financial market from 2008 to 2019. In contrast, our research provides a distinctive perspective, focusing on the US financial market, which exhibits disparities from the Chinese financial market. Notably, the US financial market boasts higher capitalization, and its fluctuations can reverberate globally. Our study, therefore, broadens the understanding initially presented by Guo and Zhang (2023) by examining a different financial market context. Second, we contribute to the FinTech literature by building a novel measure of FinTech adoption using media attention to the FinTech-related news of banks. Prior studies have also used media attention to measure banks' FinTech development, given the lack of an integrated index in this area (Deng et al., 2021; Wang et al., 2020). As an extension of the current measurement of banks' FinTech adoption,[1] we adopt a different measure to capture this. Specifically, we use media FinTech news and disclosure related to banks to measure FinTech development at the individual bank level because media news plays a crucial information transmission role between corporations and the public. We also consider that media attention to the FinTech news of banks could be a rich source for measuring banks' FinTech adoption because the public attention to a specific area is reflected in social media news (Askitas & Zimmermann, 2009, 2015).

Third, this study contributes to the existing literature on the effect of a crisis on bank lending. Prior studies have shown that banks reduce their lending and liquidity creation in times of financial crises (Acharya et al., 2018; Çolak & Öztekin, 2021; Nguyen et al., 2020). Our study presents a new perspective on the responses of banks that adopted FinTech to a financial crisis - banks that had higher levels of FinTech adoption created less liquidity during the COVID-19 pandemic period. Thus, we contribute a unique perspective on the role of FinTech development to the literature.

The remainder of this study is structured as follows. Section 2 reviews the related literature and builds the hypotheses. Section 3 presents the data source, variable definitions, and summary statistics. Section 4 describes the baseline analysis model and the main findings. Section 5 discusses endogeneity tests. Section 6 includes robustness checks and Section 7 concludes this study.

[1] For instance, we extend the studies of Deng et al. (2021) and Wang et al. (2020), who used factor analysis to construct FinTech indexes by using media news.

2. Literature review and hypothesis development

2.1. FinTech development and the banking sector

The term FinTech is a combination of two terms: finance and technology. FinTech refers to technology that provides new and advanced financial services to users. It plays a critical role in facilitating corporations' operations and promoting rapid economic growth. Further, it has drawn considerable attention from the public, the private sector and academics (Goldstein et al., 2019; Thakor, 2020). The rapid development of the FinTech industry has garnered heightened attention and attracted more investment from the capital market, particularly from the banking sector (Li et al., 2023). FinTech is defined as various advanced financial applications (e.g., digital, cloud and big data) that enhance firms' service and governance abilities (Fuster et al., 2019; Gai et al., 2018; Goldstein et al., 2019; Wang et al., 2021). Internet-based technology has been widely adopted in the industry and thus a dominant type of FinTech (Chen, 2016). For example, the growth of digital payments, online lending and mobile internet have improved financial inclusion in the community by enabling firms to provide highly accessible services to their customers (Chen, 2016; Maskara et al., 2021; Senyo & Osabutey, 2020). Furthermore, Tan et al. (2023) found that banks' FinTech adoption promote corporations' innovation.

Researchers have identified four benefits of FinTech to the banking industry. First, it enhances banks' ability to increase credit supply to small and medium enterprises (Sheng, 2021). FinTech lenders have an approximately 20% faster mortgage processing time than traditional lenders (Fuster et al., 2019). Further, FinTech-based financial inclusion is negatively associated with banks' risk-taking in Organisation of Islamic Cooperation countries (Banna et al., 2021). Buchak et al. (2018) illustrated that FinTech lenders serve creditworthy borrowers, unlike shadow banks, by adopting effective, advanced business analysis models. Second, blockchain can play a new intermediary role in the financial market, similar to that of crowdfunding platforms (Cai, 2018). Cong and He (2019) highlighted that smart contracts cause lower levels of information asymmetry and increase welfare and consumer surplus by increasing competition and the barriers to entry. Third, the application of big data disproportionately benefits large firms because these firms are able to generate more data for investors to analyse (Begenau et al., 2018). Thus, investors can analyse the vast data to increase the number and accuracy of their forecasts and reduce stock return volatility. Fourth, banks' FinTech adoption brings a series of technological advantages. Specifically, these banks have higher levels of work efficacy and service quality because FinTech provides accessible and easy-to-use functions to their employees and customers (Chen et al., 2021; Zhao et al., 2022).

Nevertheless, the current literature has provided mixed evidence on the nature of the association between FinTech adoption and bank performance or risk taking. That is, a few studies have asserted that banks that have higher levels of FinTech adoption exhibit lower levels of risk taking (Cheng & Qu, 2020; Deng et al., 2021; He et al., 2023; Wang et al., 2023; Zhang et al., 2023). For instance, Cheng and Qu (2020) used data from 2008 to 2017 in China to analyse whether banks' FinTech adoption could reduce their credit risk. They found that banks that have a high level of FinTech adoption are associated with lower credit risk. Zhang et al. (2023) similarly found that banks' FinTech adoption alleviates their credit risks. The study of He et al. (2023) suggested that banks with higher levels of FinTech adoption have lower levels of risk taking. Moreover, Wang et al. (2023) found that banks that have improved FinTech input have lower non-performing loans. However, there is evidence of a positive association between FinTech adoption and risk taking. For example, Wang et al. (2020), who explored the relationship between the FinTech adoption of banks in China and their risk taking by employing data for 2011 to 2018, found that such adoption increases banks' risk taking. In addition, the authors showed that the relationship is convex, specifically, an inverted-U shape, which suggests that banks may suffer higher levels of risk in the initial stage of FinTech development but this risk decreases when their FinTech development levels mature.

Overall, the literature has focused mainly on the relationship between banks' FinTech adoption and performance, primarily in China's banking sector, and the impact of the FinTech industry on China's banking sector. Similarly to the present study, Guo and Zhang (2023) found a positive correlation between banks' FinTech adoption and their liquidity creation. In their study of the Chinese market, they used a web crawler and text mining to construct a FinTech index, which was similar to the methods used in prior studies. However, we explore the relationship in the US market, which differs considerably from the Chinese market because it is in a capitalist country. Moreover, shocks from the US financial market can spillover to other countries; thus, the significant differences raise the question of whether the conclusion differs depending on which of the two financial markets is considered. Therefore, we address this knowledge gap by evaluating the nature of the association between FinTech adoption by US banks and their liquidity creation.

2.2. Bank liquidity creation and financial crisis

Financial intermediation theory states that liquidity creation in the economy and society is a major function of banks. Prior studies have investigated the determinants of bank liquidity creation. This section focuses on the literature on bank liquidity creation from two perspectives: bank and macroeconomic characteristics.

Prior studies have demonstrated that bank liquidity creation is significantly associated with various bank characteristics. For instance, Díaz and Huang (2017) found that bank liquidity is positively associated with improved internal bank governance (e.g., CEO characteristics, compensation structure and ownership), and that the effect is more pronounced during a financial crisis period and for large banks. Similarly, Huang et al. (2018) noted that large banks that have optimistic CEOs are highly likely to create more liquidity, and a financial crisis magnifies the positive effect. Zheng et al. (2023) showed that banks' liquidity creation is positively associated with their corporate social responsibility performance, and the results are consistent during a financial crisis period. Furthermore, liquidity creation may expose banks to failure because of sudden deposit withdrawals (Allen & Gale, 2004; Allen & Santomero, 1997; Diamond & Dybvig, 1983; Diamond & Rajan, 2011). However, Zheng et al. (2019) found that the liquidity creation of US banks is negatively correlated with their failure risks, and higher levels of bank capital magnifies this negative relationship. Other studies have offered mixed findings on the relationship between bank' liquidity creation and capital (Berger & Bouwman, 2009; Fu et al., 2016; Gorton & Winton, 2017; Horváth et al., 2014; Tran et al., 2016) and bank competition (Horvath et al., 2016; Jiang et al., 2019).

Moreover, numerous studies have investigated the relationship between bank liquidity creation and macroeconomic characteristics. For instance, Beck et al. (2023) argued that bank liquidity creation plays a vital role in fostering economic growth through the stimulation of tangible investment. Davydov et al. (2021) showed that bank liquidity creation is negatively correlated with system risk. Berger and Bouwman (2017) revealed that banks create more liquidity before a financial crisis. They also showed that the effect of monetary policy on banks' liquidity creation is small and restricted to small banks. Further, this effect is weakened during a financial crisis period. However, Chatterjee (2018) indicated that banks reduce their liquidity creation after a financial crisis. In summary, banks may create less liquidity during periods of financial crisis.

2.3. Hypothesis development

This section presents three research hypotheses regarding the effect of banks' FinTech adoption on their liquidity creation. On the one hand, we argue that banks that enhance their level of FinTech adoption increase their liquidity creation for two reasons. First, these banks achieve more comprehensive financial inclusion by providing highly accessible applications to serve their customers, who can request or demand the banks' services at any time and from anywhere. In the current era of digitisation, mobile applications are increasingly replacing bank branches by providing digital services to customers (Acharya et al., 2008; Gabor & Brooks, 2017). Banks are adopting mobile technologies (e.g., online banking and mobile payments) to increase the accessibility of their business services to customers, who can apply for these services without visiting a branch. Moreover, banks can adopt other types of FinTech to increase their inclusion in the community. For example, banks are using robo-advisors in their online services to provide 24/7 program-based services for their customers at lower operating costs (Jung et al., 2018). Venkatesh et al. (2003) proposed a Unified Theory of User Acceptance Technology (UTUAT) model that explains the factors that affect users' intentions to use internet banking. One of the factors is known as effort expectancy, which refers to the fact that users are more willing to use the technology if it is easy to learn and use. Martins et al. (2014) further affirmed the impact of user' expectancy on their intentions to use internet banking. Specifically, banks can increase their transaction and lending activities by providing easy-to-use applications to their customers who demand convenience in accessing to banks' services. Therefore, banks can create more liquidity by serving more customers through the wider coverage allowed by online services.

Second, banks that have enhanced FinTech development have less information asymmetry among their borrowers, which, in turn, increases liquidity creation by providing loans to those underrated borrowers. Studies of Chinese banks have revealed that greater levels of FinTech adoption have an inverse U-shaped effect on bank risk taking (Wang et al., 2020), lowers credit risk (Cheng & Qu, 2020), lowers risk-taking (He et al., 2023), lowers non-performing loans (Wang et al., 2023) and improves performance (Li et al., 2017; Phan et al., 2020). The adoption of FinTech in the banking sector has brought about a series of technological innovations to banks. For instance, the adoption of AI and big data applications improves banks' risk management and credit access to borrowers by optimising banks' traditional business model, which further increases banks' analysis accuracy in lending decisions and risk forecasts (Hung et al., 2020; Ozgur et al., 2021; Sadok et al., 2022; Wang et al., 2021). Following the 'Information Asymmetry Theory' (Akerlof, 1970), banks encounter difficulty in gathering sufficient information about their borrowers. The study of Gou et al. (2023) showed that the innovation of digital technology increases banks' lending through the mitigation of information asymmetries. As a result, they may refrain from lending to these borrowers who are classified as underrated. The adoption of these technologies enables banks to effectively detect and collect adequate information from the borrowers who were previously underrated by them. In addition, banks employ advanced data processes and risk management models to optimise lending procedures to make their services (e.g., loans and portfolios) more efficient and accurate. Hence, banks that have advanced FinTech adoption create more liquidity by mitigating information asymmetry and efficiently managing their abundant customer data.

On the other hand, we argue that banks that have better FinTech adoption may create less liquidity and provide three perspectives to support this argument. First, banks create less liquidity through improved screening and monitoring quality, resulting in less lending by removing low-quality borrowers. Banks that have better FinTech adoption tend to be more careful when engaging in lending activities. Their use of FinTech in their operating business model leads banks to evaluate borrowers' qualifications using better measurements instead of soft information (Sedunov, 2017).[2] Meanwhile, banks' adoption of FinTech could reduce the potential risk of their lending activities by enhancing their ability to monitor borrowers' latent risk behaviours. The potentially risky borrowers might not be able to repay loans and their collateral might be overrated compared with the intrinsic value. Hence, banks take on more default risk if they engage in a large number of low-quality lending activities. Conversely, banks that have better FinTech adoption may have a higher probability of having high-quality loans, given that FinTech applications could reduce banks' default and information risks, which reduces their credit risk (Kim et al., 2018). Therefore, banks create less liquidity because they tend to absorb high-quality assets via FinTech applications instead of creating liquidity from lower-quality assets or borrowers to prevent external shocks.

Second, FinTech improves banks' ability to evaluate short-term borrowers, who generally borrow small amounts, while decreasing the need for lending to long-term borrowers with lower credit quality. Ultimately, this results in less lending and hence low liquidity creation for banks that have adopted FinTech. According to the information asymmetry theory (Akerlof, 1970), there is an information asymmetry between banks and borrowers, leading banks to establish long-term relationships with borrowers to obtain specific

[2] Soft information is information about opinions, ideas, rumours, economics projections, statements of management's future plans and market commentary (Bertomeu & Marinovic, 2016).

information from them. This is also known as relationship lending.[3] Banks that have better FinTech adoption can efficiently gather specific information about borrowers in a shorter period. Hence, the banks can avoid establishing long-term contracts to filter out low-quality credit borrowers and identify worthy borrowers using better FinTech adoption. As a result, banks may create less liquidity from the lending activities.

Third, FinTech adoption involves a significant investment that might leave less amount of a bank's available limited resources for liquidity creation purposes. When banks decide to adopt FinTech applications in their businesses, they need to invest in their FinTech projects continually to ensure that the FinTech application remains operational. Overall, the investment in FinTech is costly to banks, especially in the initial stage (Wang et al., 2020). Not all banks that adopt FinTech are willing to develop their own FinTech applications because this approach is too costly. However, they may cooperate with technology firms to obtain licences or pay subscription fees for the FinTech application (Murinde et al., 2022). The extra costs incurred by banks for FinTech applications result in them having fewer resources with which invest. For instance, banks may engage in fewer lending activities or other investments. In line with these arguments, we propose the first hypothesis in an alternative form as follows:

Hypothesis 1a. (H1a): Banks that have greater levels of FinTech adoption create more liquidity.

Hypothesis 1b. (H1b): Banks that have greater levels of FinTech adoption create less liquidity.

We argue that banks that adopt FinTech create less liquidity during a financial crisis for two reasons. First, banks generally create less liquidity during an economic recession (Chatterjee, 2018; Davydov et al., 2021). They reduce their liquidity creation to minimise their risk exposure by reducing credit lending (Acharya et al., 2018; Nguyen et al., 2020). Particularly, banks that have high levels of liquidity creation are exposed to a higher risk of failure during a financial crisis (Zheng et al., 2019). Moreover, during the COVID-19 pandemic period, banks experienced reduced levels of lending and consumer expenditure owing to unemployment and disrupted consumption patterns (Andersen et al., 2022; Çolak & Öztekin, 2021). In terms of the adoption of FinTech by banks, it is important to note that they will have fewer resources available for investment, such as engaging in lending activities. This reduction in resources is attributed to the inherent costs associated with FinTech adoption, as highlighted by Wang et al. (2020). Consequently, the decrease in lending activities results in a corresponding reduction in their capacity to create liquidity. Therefore, banks create less liquidity during a financial crisis, such as that induced by the COVID-19 pandemic.

Second, banks that have advanced FinTech development remained operational during this pandemic period; hence, these banks maintained their internal governance and business operation functions to maintain their lending or portfolio at the optimal position by using advanced business analysis models and algorithms during lockdown periods. The lockdown policies included bans on social activities, which resulted in limited face-to-face services at bank branches. These policies also forced bank employees to work from home, which reduced their work efficiency and productivity (Farooq & Sultana, 2021; Kramer & Kramer, 2020; Mustajab et al., 2020). Consequently, banks were less likely to respond appropriately to the financial recession caused by the COVID-19 pandemic because their governance and businesses were temporarily adversely affected because of the lockdown policies. Nevertheless, banks that had developed FinTech maintained their governance and business functions through online applications, minimising external shocks by adjusting their portfolios appropriately and lowering the default rate of high-quality assets. For example, the application of digital platforms has prevented employees from decreasing their digital knowledge sharing and creative performance when working from home during this pandemic period (Tønnessen et al., 2021).

Third, the adoption of analytical FinTech applications (e.g., AI and big data) enabled banks to use advanced business analysis models and algorithms to absorb high-quality assets, which reduced the probability of defaults by borrowers during the pandemic period. Specifically, the application of big data and AI in the banking sector enhances banks' effectiveness in modelling and tracking customers' (e.g., lenders and borrowers) financial status and probability of failure to repay, by maximising the use of customers' personal information leading to less lending (Goldstein et al., 2021). Therefore, we propose the second hypothesis as follows:

Hypothesis 2. (H2): Banks that have greater levels of FinTech adoption created less liquidity during the COVID-19 pandemic period.

Finally, we argue that the various types of FinTech have varying effects on banks' liquidity creation activities. First, banks can use internet-based FinTech to create more liquidity by providing highly accessible services to their customers, who are able to use banks' services via online applications (Chen et al., 2021). Specifically, this type of FinTech increases banks' financial inclusion, which increases their ability to conduct business with customers who can apply for loans or other services online. Customers of a bank that provides highly accessible to services have a high level of willingness to apply if its branches do not cover their living area or they are travelling. Hence, banks can create more liquidity by adopting internet-based FinTech. However, internet-based FinTech enhances banks' information-sharing abilities through various departments, which enables banks to share customers' information for analysis and communications in a more efficient and timely manner. The high level of information efficacy not only reduces banks' probability of inaccuracy in customers' risk analysis and adjustments of investment portfolios but also simplifies tracking customers' data and flow in different departments. Hence, internet-based FinTech causes banks to create less liquidity because they can conduct timely and accurate analysis of their borrowers' credit analysis and enhance the linkage between different FinTech applications.

Second, blockchain technology reduces banks' information asymmetry and credit rationing problems through decentralised

[3] Relationship lending refers to the notion that lenders continually offer long maturity financing and less frequent repayments to the same borrower to obtain the specific information about the borrower and earn interest on it even during a crisis or unprofitable period (Bharath et al., 2011; Bolton et al., 2016; Chan et al., 1986; Petersen & Rajan, 1995).

consensus and information distribution (Cong & He, 2019; Wang et al., 2019). Thus, banks are more efficient in accessing information on their internal governance system, repayment system and borrowers' and lenders' activities (e.g., through smart contracts and a distributed ledger). Further, banks that adopt blockchain technology manage transactions through mobile applications more efficiently. Hence, these banks may create more liquidity because they fund underrated borrowers who are not able to provide collateral. However, the adoption of blockchain may lead banks to create less liquidity through enhanced data management, contracting and security. The decentralised technology of blockchain can make banks' databases unbreachable or unmodifiable, which further leads to their databases having lower levels of probability of manipulation by internal fraud activities of conducting suspicious lending (Navaretti et al., 2018). Verifying and validating specific lending and borrowing activities in distributed ledgers allows banks to maintain a record of successful debt repayment and debt default (Wang et al., 2019).

Third, banks that adopt cloud and AI applications are capable of processing vast amounts of data on lending and portfolio activities within a short period through their increased and secure access to data storage platforms (Avram, 2014; Jung et al., 2018; Ozgur et al., 2021). For instance, the adoption of AI-based robo-advisor software enhances banks' financial inclusion by enabling them to provide uninterrupted online services to their customers. This allows the banks to meet the demands of more customers within a shorter period compared with traditional banking methods. Hence, banks that adopt AI can create more liquidity through their high levels of financial inclusion. Further, cloud-based FinTech is related to internet-based FinTech because cloud applications provide banks with online data storage and analysis tools. However, the use of AI and cloud applications can also increase banks' abilities to detect and terminate overrated borrowers' loans and relationship lending and further increase their risk management abilities. Moreover, the development of AI and cloud FinTech is costly, especially for the banks that develop and build their own FinTech applications, which results in fewer resources that can be used for investment (Fethi & Pasiouras, 2010; Wang et al., 2020). Therefore, banks may create less liquidity by adopting AI and cloud applications. Specifically, banks' liquidity creation differs according to the type of FinTech development they adopt; therefore, we propose the third hypothesis as follows:

Hypothesis 3. (H3): The liquidity creation of banks differs between different types of FinTech adoption.

3. Empirical setting

3.1. Data sources and variables

Our sample includes the top 300 BHCs in the US from Q1 2015 to Q2 the 2021. The selection of these BHCs is due to their market capitalisation in Q1 2015. We obtain data from several sources. Specifically, quarterly financial data, including data on all the components of liquidity creation, are from the FR Y–9C reports in the Federal Reserve of Chicago database. Data on BHC-specific characteristics are from FR Y–9C reports and are calculated manually. FinTech news data are sourced from Refinitiv Workspace News function, which provides counts for various news topics related to BHCs. The final data set contains 6236 bank-quarter observations across 300 unique BHCs from Q1 2015 to Q2 2021. All continuous variables are winsorised at the 1% and 99% levels.

3.2. Measures of liquidity creation

The liquidity creation of BHCs is the main dependent variable. We follow Berger and Bouwman (2009), who proposed a comprehensive measurement to calculate individual commercial banks' liquidity creation for on-balance sheet and off-balance sheet activities. They followed a three-step procedure to construct a bank's liquidity creation. The components of this measure are presented in Appendix B. The first step is to categorise banks' on-balance and off-balance sheet activities into liquid, semi-liquid, and illiquid activities. The activities include assets, liabilities, equity, derivatives and guarantees. Second, the on-balance and off-balance sheet activities identified in the first step are assigned weights of +0.5, −0.5 and 0. According to the modern theory of financial intermediation, banks create liquidity by transforming illiquid assets into liquid liabilities through on-balance sheet activities. Specifically, banks create liquidity by financing liquid liabilities (e.g., deposits) to customers who supply illiquid assets (e.g., loans). Thus, a positive weight of +0.5 is assigned to illiquid assets and liquid liabilities. Similarly, a negative weight of −0.5 is given to liquid assets, illiquid liabilities and equity because banks eliminate liquidity when they use illiquid liabilities (e.g., subordinated debt) or equity to finance liquid assets (e.g., Treasury securities). A weight of 0 is assigned to all semi-liquid assets and liabilities (e.g., consumer loans). The weight allocations for off-balance-sheet activities are consistent with those assigned to functionally similar on-balance sheet activities. Finally, the sum of all the weighted activities identified in the prior two steps is total bank liquidity creation, $lc\_total_{i,t}$, which is the primary dependent variable in all the empirical analyses.

In addition, we consider four other bank-specific liquidity creation measures: *lc_on*, *lc_off*, *lc_asset*, and *lc_lia*: *lc_on* is computed using only on-balance sheet items, while *lc_off* is computed using only off-balance-sheet activities. Similarly, *lc_asset* is computed using only asset-side liquidity creation items while *lc_lia* is computed using only liability-side liquidity creation activities. Following Berger and Bouwman (2009), our main proxy for liquidity creation is *lc_total* divided by gross total assets (GTA)[4] where *lc_total* is computed as follows:

[4] GTA equals total assets plus allowances for loan and lease losses and the allocated risk transfer.

$$
\begin{aligned}
lc\_total = {} & 0.5 \times (illiquid\ assets + liquid\ liabilities + illiquid\ guarantees) + 0 \\
& \times (semiliquid\ assets + semiliquid\ liabilities + semiliquid\ guarantees) - 0.5 \\
& \times (liquid\ assets + illiquid\ liabilities + equity + liquid\ guarantees + liquid\ derivatives)
\end{aligned} \tag{1}
$$

3.3. Measures of FinTech variables

We propose a new FinTech index to measure BHCs' FinTech adoption using the Refinitiv Workspace News function. The database includes news article titles and the main text from various online news sources. Most of the news items are published as daily news article on online platforms and written by reporters (e.g., Thomson Reuters News, CNBC news and International Financing Review News).[5] Prior studies have generally used five FinTech type applications, namely, AI, blockchain, big data, cloud and internet (Cheng & Qu, 2020; Wang et al., 2021). However, this study uses only four types of FinTech applications and excludes big data applications because the quantity of news related to big data is relatively small compared with the other types in the Refinitiv Workspace database. Furthermore, big data applications form an integral part of AI and cloud applications because they serve as a foundation for these technologies. The function contains a number count of news headlines for the four FinTech categories, AI, blockchain, cloud and internet, by using web crawler and text mining techniques. It also includes alternative topics related to these four categories. Specifically, news headlines on the AI, blockchain and cloud are searched for by the topic provided by the Refinitiv Workspace while those on the internet are searched for using mixed search methods (e.g., topics and keywords).[6] The topic search method refers specifically to the range of news related to a specific FinTech type. It automatically contains all the news related to the FinTech types. For instance, news relating to robo-advisor techniques is categorised as AI even when the news headline does not contain the word AI in the text. Nevertheless, the keyword search method only checks whether the headline contains specific text. The assumption is that a higher value of FinTech index indicates that the BHC has an advanced level of FinTech development. We search for the BHCs' FinTech news counts in all periods and merge the sample into a quarterly frequency one. Then, we construct a FinTech index to measure BHCs' FinTech development level as follows:

$$
fintech_{i,t} = \ln\left(1 + \sum News_{i,t}\right) \tag{2}
$$

where $fintech_{i,t}$ represents BHC i's overall FinTech adoption level at time t, and *News* refers to the total news count related to the BHCs' four FinTech categories. Prior studies have used FinTech news as a primary measure for banks' FinTech adoption (Cheng & Qu, 2020; Wang et al., 2020). In addition, we consider the effect of various types of FinTech adoption on liquidity creation. Therefore, we further calculate the FinTech index for each of the four categories. These four FinTech type indexes are similar to Equation (2) while the news count for these four FinTech indexes includes each FinTech category only. For instance, the AI index covers only the news related to AI of BHC i at time t.

3.4. Measures of COVID-19 and FinTech industry variables

Data on the COVID-19 variable are collected from the John Hopkins COVID-19 database, which contains detailed data on COVID-19 infections at the state level. Following Ding et al. (2020), we calculate the growth rate of the cumulative confirmed cases caused by the COVID-19 pandemic (*gc_covid*) as follows:

$$
gc\_covid_{i,j,t} = ln\left(1 + cumulative\ cases_{i,j,t}\right) - ln\left(1 + cumulative\ cases_{i,j,t-1}\right) \tag{3}
$$

where i, j and t stand for BHC, state and quarter, respectively; state refers to the location in which the BHC operates at the state level specifically; $cumulative\ cases_{i,j,t}$ represents the cumulative confirmed cases of BHC i's headquarter state j at the end of quarter t.

3.5. Control variables

In line with prior studies, we include six bank-specific control variables in our multivariate analysis in this study. Following the studies of Berger and Bouwman (2009), Boyd et al. (1993) and Horvath et al. (2016), we control for three risk measurements that might affect bank liquidity creation, namely, credit risk, z-score and earnings volatility. The credit risk (*cr*) is computed as the sum of the BHCs' Basel I risk-weighted assets and off-balance sheet activities divided by GTA. The z-score (*zs*) is used as the proxy of default risk and calculated as the return on assets plus the ratio of equity capital to GTA divided by the standard deviation of the return on assets. Earnings volatility (*ev*) is measured by the standard deviation of the bank's return on assets over the previous 12 (minimum: 8) quarters. We further follow the existing literature to control for two bank-level variables specifically that might affect banks' liquidity creation (Berger & Bouwman, 2009; Díaz & Huang, 2017; Jiang et al., 2019; Nguyen et al., 2020). Return on assets (*roa*) as a measure of bank profitability is computed as the ratio of net income to total assets. Bank size (*bs*) is the natural logarithm of GTA. Capital ratio

[5] More detail about the news articles is included in Appendix D.

[6] Several search methods can be used for the internet variable, unlike for other variables. Specifically, searches can be conducted on the topics of the Internet of Things, digital payment and digital assistance. Two keywords can also be searched for, namely, online banking and digital banking.

(*capr*) is the ratio of equity capital to total assets. The variable definitions are provided in Appendix A.

3.6. Summary statistics

The descriptive statistics of the main variables are reported in Panel A of Table 1. The mean values of the dependent variables, $lc\_total_{i,t}$, $lc\_on_{i,t}$, $lc\_off_{i,t}$, $lc\_asset_{i,t}$ and $lc\_lia_{i,t}$ are 0.4879, 0.3634, 0.1230, 0.1244 and 0.2389, respectively, which are comparable with those reported in prior studies (Berger & Bouwman, 2009; Davydov et al., 2021; Zheng et al., 2019). For the main independent variable, the FinTech index ($fintech_{i,t}$), the mean is 0.0704, the minimum value is 0 and maximum value is 2.0794. Similarly to *fintech*, for the subcategories of *fintech,* the mean value is close to that of *fintech* and ranges between 0 and 3. Turning to the COVID-19 variable, the mean of $gc\_covid_{i,j,t}$ is 0.2115 and its maximum value is 3.4025. In addition, Figs. 1 and 2 present the tendency of banks' FinTech index and FinTech type indexes from the first quarter of 2015 to the second quarter of 2021. As shown in Fig. 1, banks' FinTech index growth rapidly during the period. It is also worth noting that overall FinTech grows suddenly and significantly after the first quarter of 2020. This indicates that the unexpected COVID-19 pandemic accelerated and boosted FinTech development in the banking sector. Fig. 2 depicts the trend of each type of FinTech during the period. The significant growth observed in the development of different FinTech applications in our sample aligns with the trend of the overall FinTech index in Fig. 1, and is particularly noticeable after the first quarter of 2020. However, there is a significant decline in the FinTech indexes after the first quarter of 2020 in Figs. 1 and 2. This might be because not all banks are capable of deciding to invest in FinTech at the same time. Some small banks may want to wait and observe the FinTech adopted banks' performance of the banks that adopted FinTech because the FinTech applications are costly, and such investments are risky especially during a period of high economic and policy uncertainty.

Panel B of Table 1 reports the correlation coefficients of the main dependent variables and independent variables in the regression models. The significant negative correlation coefficients between $lc\_total_{i,t}$, $lc\_on_{i,t}$, $lc\_asset_{i,t}$ and $lc\_lia_{i,t}$ and $fintech_{i,t}$ provide univariate evidence that banks that had greater levels of FinTech adoption created less liquidity according to any of our four liquidity creation measures. Nevertheless, the correlation between $lc\_off_{i,t}$ and $fintech_{i,t}$ is significant and positive. The likely reason is that banks were able to optimise their off-balance sheet portfolio (e.g., diversities) via FinTech applications.

4. Empirical results

4.1. Main results

The baseline regression model to test *H1*, which is associated with the impact of FinTech adoption on bank liquidity creation is as follows:

$$liqudity\_creation_{i,t} = \beta_0 + \beta_1 fintech_{i,t} + \vartheta' bank_{controls} + \gamma_i + \delta_t + \varepsilon_{i,t} \quad (4)$$

where $liquidity\_creation_{i,t}$ as the main dependent variable in this study represents the liquidity created by an individual BHC *i* at quarter *t*. The main independent variable in the regression model is $fintech_{i,t}$, which represents bank *i*'s FinTech adoption level at time *t*. Moreover, control variables at the BHC level are included in the regression models. In addition, to mitigate the impact of unobservable BHC-level individual effects and time trend effects on the results, we control for BHC fixed effects (γ_i) and year-quarter fixed effects (δ_t). Further, we adopt heterogeneity robust standard errors clustered at the BHC level ($\varepsilon_{i,t}$) to address autocorrelation and heteroscedasticity issues.

Table 2 presents the baseline regression results of this study. Panel A of Table 2 presents the results without the control variables. The coefficient on $fintech_{i,t}$ is negative and statistically significant for $lc\_total_{i,t}$, $lc\_on_{i,t}$ and $lc\_asset_{i,t}$ in Columns 1, 2 and 4. These results suggest that banks that had better FinTech adoption created less total, on-balance sheet and asset-side liquidity. Panel B of Table 2 includes the control variables in the model. The results are consistent with Panel A, hence supporting to *H1b* that banks that have greater FinTech adoption create less liquidity. In terms of economic magnitude, a one-standard-deviation increase in banks' FinTech adoption (=0.3211) resulted in a decline of 0.75% in total liquidity creation[7] and 0.48% and 1.27% in on-balance sheet and asset-side liquidity creation, respectively.

Regarding the BHC-level control variables, we note several important relationships. First, banks created more liquidity if they had higher levels of credit risk ($cr_{i,t}$), as shown in Columns 1 to 4. Second, the significant and negative coefficient on $zs_{i,t}$ in Column 3 indicates that banks that had high levels of default risk were more likely to create less liquidity. Third, banks created less liquidity if they had higher earnings volatility ($ev_{i,t}$), as indicated in Columns 1, 2, and 4. Fourth, the significant and positive coefficient on $roa_{i,t}$ in Columns 1 and 3 suggests that more profitable banks produced less total and off-balance sheet liquidity. Fifth, large banks created less liquidity in total and liability-side items, as shown in Columns 1 and 5. Sixth, banks created more liquidity if they had a higher levels of capital ratio ($capr_{i,t}$), as indicated in Columns 3 and 4. The opposite effect is found for liability-side activities, as shown in Column 5.

Next, we build the following regression model to test *H2*, that is, to capture the effect of the COVID-19 pandemic on the relationship

[7] The economic magnitude is calculated as follows: $(-0.0114 \times 0.3211)/0.4879 = -0.0075$, where 0.3211 is the standard deviation of $fintech_{i,t}$, −0.0114 is the regression coefficient on $fintech_{i,t}$ for total liquidity creation in Column 1 of Panel B and 0.4879 is the mean value of $lc\_total_{i,t}$. The calculations are the same for the other variables.

Table 1
Descriptive statistics
Note: Panel A reports summary statistics of all variables in this study. Panel B reports Pearson correlation matrix of main variables. *, **, *** represents significance at 10%, 5% and 1% level, respectively. Appendix A includes the definitions of all variables.

Panel A: Summary statistics

VARIABLES	(1)	(2)	(3)	(4)	(5)
	n	mean	sd	min	max
lc_total	6236	0.4879	0.1855	−0.1004	0.9711
lc_on	6236	0.3634	0.1512	−0.1735	0.6120
lc_off	6236	0.1230	0.0731	0.0029	0.5169
lc_asset	6236	0.1244	0.1302	−0.2666	0.3753
lc_lia	6236	0.2389	0.0835	−0.0875	0.3696
fintech	6236	0.0704	0.3211	0.0000	2.0794
ai	6236	0.0093	0.0799	0.0000	0.6931
blockchain	6236	0.0349	0.2118	0.0000	1.6094
cloud	6236	0.0053	0.0919	0.0000	3.6376
internet	6236	0.0283	0.1628	0.0000	1.0986
cr	6236	0.8476	0.1833	0.0810	1.3131
zs	6236	2.1738	1.0646	−0.0556	4.4918
ev	6236	0.3458	0.2003	0.1294	1.4157
bs	6236	15.9110	1.6674	13.4186	21.4046
roa	6236	0.6026	0.3777	−0.1393	1.8924
capr	6236	0.1147	0.0251	0.0682	0.2048
gc_covid	6236	0.2115	0.6270	0.0000	3.4025

Panel B: Correlation matrix of main variables

	lc_total	lc_on	lc_off	lc_asset	lc_lia	fintech
lc_total	1					
lc_on	0.8986***	1				
lc_off	0.6113***	0.2130***	1			
lc_asset	0.7937***	0.8367***	0.2392***	1		
lc_lia	0.4080***	0.5221***	0.0171***	−0.0247	1	
fintech	−0.1789***	−0.3303***	0.2123***	−0.2486***	−0.2349***	1

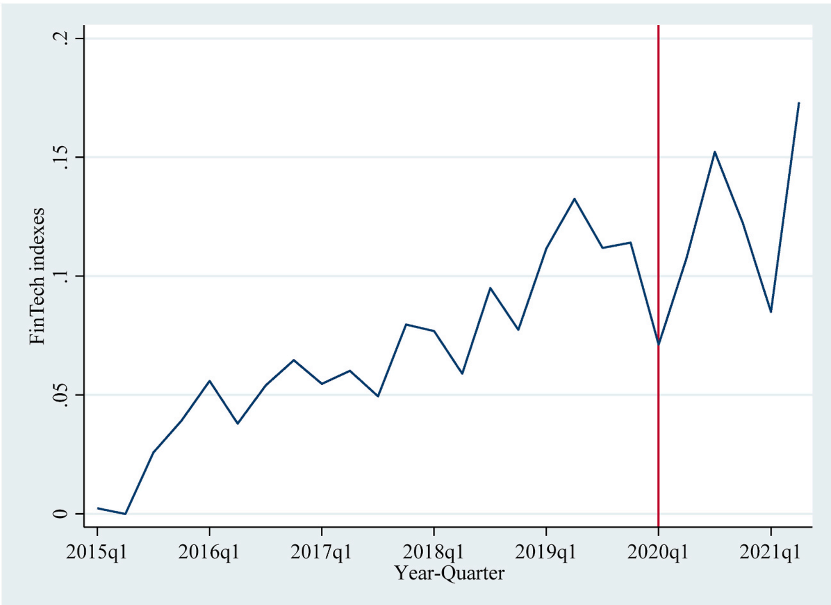

Fig. 1. Average value of FinTech index.

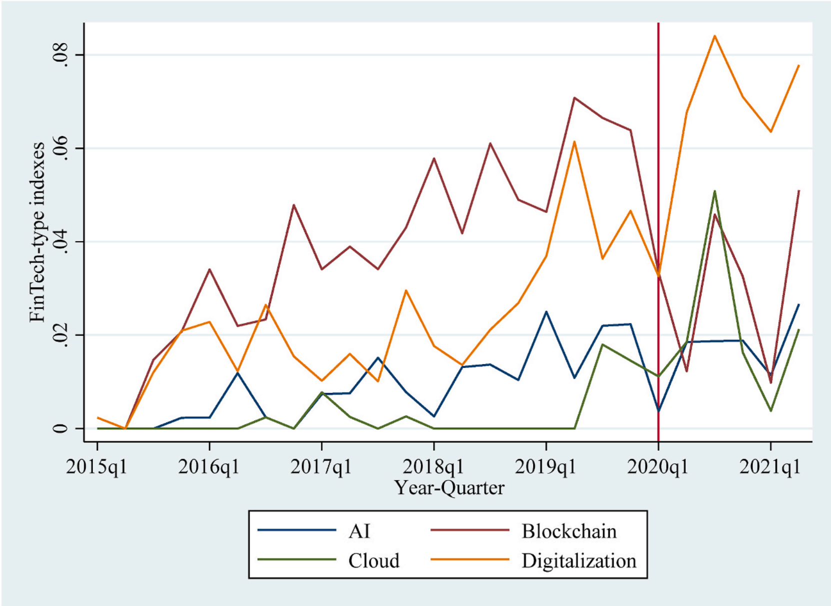

Fig. 2. Average value of FinTech types indexes.

between BHCs' FinTech adoption and their liquidity creation[8]

$$liqudity\_creation_{i,t} = \beta_0 + \beta_1 fintech_{i,t} + \beta_2 gc\_covid_{i,j,t} + \beta_3 fintech_{i,t} \times gc\_covid_{i,j,t} + \vartheta' bank_{controls} + \gamma_i + \delta_t + \varepsilon_{i,t} \tag{5}$$

The coefficient on the interaction term $fintech_{i,t} \times gc\_covid_{i,j,t}$ is our key focus. Table 3 reports the results of Equation (5). The coefficient on the interaction term $fintech_{i,t} \times gc\_covid_{i,j,t}$, is significant and negative for $lc\_total_{i,t}$, $lc\_on_{i,t}$ and $lc\_asset_{i,t}$ in Columns 1, 2 and 4, respectively. These results convey that the negative impact of FinTech adoption on bank liquidity creation (total, on-balance sheet and asset-side liquidity creation) was magnified during the COVID-19 pandemic. In terms of economic magnitude, a bank that had a one-standard-deviation increase in FinTech adoption (=0.3211) experienced a decline in total, on-balance sheet and asset-side liquidity creation by 0.76%, 1.05% and 3.20%, respectively, during this pandemic period. Therefore, *H2* is accepted.

Finally, using Equation (4), we test *H3* by replacing $fintech_{i,t}$ with different FinTech types. Panel A of Table 4 shows the results of the effect of the FinTech subcategories on total liquidity creation. The significant and negative coefficients on $cloud_{i,t}$ and $internet_{i,t}$ in Columns 3 and 4 demonstrate that banks that had better cloud and internet adoption reduced their total liquidity creation. Regarding economic magnitude, the results imply that banks that had a one-standard-deviation increase in cloud (=0.0919) and internet (=0.1628) adoption experienced a decrease in total liquidity creation by 0.27% and 0.45%, respectively. Overall, the results suggest that the negative impact of FinTech adoption on bank liquidity creation is driven by FinTech that relates to cloud and internet.

We further analyse the mediating role of COVID-19 on the relationship between the subcategories of FinTech and liquidity creation in relation to our third hypothesis (*H3*). We estimate Equation (5) by replacing *fintech* with the FinTech types. Panel B of Table 4 reports the results. The significant and negative coefficients on $ai_{i,t} \times gc\_covid_{i,j,t}$, $blockchain_{i,t} \times gc\_covid_{i,j,t}$ and $internet_{i,t} \times gc\_covid_{i,j,t}$, in Columns1, 2 and 4 suggest that banks that had greater levels of AI (=0.0799), blockchain (=0.2118) and internet (=0.1628) adoption reduced their total liquidity creation, particularly during the COVID-19 pandemic period. The results suggest that there was a 0.35%, 0.89% and 0.59% decrease in total liquidity creation for a one-standard-deviation increase in AI, blockchain and internet FinTech adoption, respectively. One possible explanation for this is that the utilization of AI and blockchain enhances analytical capabilities while maintaining a low risk of exposure for databases through blockchain technology. Additionally, FinTech applications related to the internet play a crucial role in ensuring the operational continuity of banks' business activities.

4.2. Bank size analysis

Following Berger and Bouwman (2009), we divide our banks into three groups according to size: large, medium, and small banks.[9] Given that we consider only the top 300 BHCs, only a few banks are classified as medium and small banks. Therefore, we combine the medium and small bank groups to form a sample of small banks and conduct the following tests.

[8] The COVID-19 pandemic period considered in this study is from the first quarter of 2020 to the second quarter of 2021.

[9] The large banks are those that had GTA exceeding US$3 billion, the medium banks are those whose GTA ranged between US$3 billion and US$1 billion, and the small banks are those whose GTA was less than US$1 billion.

Table 2
Effect of FinTech adoption on bank liquidity creation
This table reports the results of equation (4) estimated using ordinary least squares techniques. The main dependent variable is the liquidity creation variables which are measured following Berger and Bouwman (2009). We specifically test five liquidity creation categories in the regression models, namely, total, on-balance sheet, off-balance sheet, asset-side and liability-side liquidity creation. The independent variable *fintech* is FinTech adoption variable for individual BHC level. A higher value of *fintech* indicates that the BHC has higher FinTech adoption. The sample encompasses 6236 bank-quarter observations of 300 US listed BHCs from the first quarter of 2015 to the second quarter of 2021. This regression model includes year-quarter and BHC level fixed effect. Appendix A includes the definitions of all variables. *, **, *** represents significance at 10%, 5% and 1% level, respectively.

Panel A: without control variables

VARIABLES	(1)	(2)	(3)	(4)	(5)
	lc_total	*lc_on*	*lc_off*	*lc_asset*	*lc_lia*
fintech	−0.0138***	−0.0057*	−0.0046	−0.0072**	0.0018
	(-2.7442)	(-1.8768)	(-1.2408)	(-2.5204)	(0.6990)
Constant	0.4521***	0.3304***	0.1187***	0.1009***	0.2293***
	(117.0683)	(115.4134)	(58.8039)	(37.3965)	(147.7612)
Bank FE	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	6236	6236	6236	6236	6236
Adjusted R-squared	0.0939	0.1307	0.0414	0.1611	0.3760

Panel B: with control variables

VARIABLES	(1)	(2)	(3)	(4)	(5)
	lc_total	lc_on	lc_off	lc_asset	lc_lia
fintech	−0.0114***	−0.0054**	−0.0029	−0.0049*	−0.0003
	(-3.3718)	(-1.9846)	(-0.9954)	(-1.7635)	(-0.1523)
cr	0.3558***	0.1308***	0.1984***	0.1290***	0.0059
	(5.3378)	(5.8348)	(4.0169)	(6.0063)	(0.9433)
zs	−0.0045	0.0003	−0.0047**	−0.0008	0.0008
	(-1.3737)	(0.1028)	(-2.2916)	(-0.3327)	(0.6836)
ev	−0.0215**	−0.0276***	0.0050	−0.0200**	−0.0067
	(-2.5385)	(-3.3761)	(0.8834)	(-2.1033)	(-1.1638)
roa	0.0235***	0.0030	0.0187***	0.0079	−0.0028
	(2.8860)	(0.5682)	(2.7804)	(1.6267)	(-0.9960)
bs	−0.0262*	−0.0153	−0.0130	0.0044	−0.0204***
	(-1.8061)	(-0.9885)	(-1.2833)	(0.2660)	(-3.3653)
capr	0.0249	−0.2374	0.2314*	0.4807**	−0.7369***
	(0.1403)	(-1.3040)	(1.8342)	(2.4563)	(-7.9814)
Constant	−12.6312***	−9.4079***	−3.0340***	−6.3652***	−2.9446***
	(-6.9385)	(-6.1510)	(-3.2375)	(-4.2250)	(-5.1098)
Bank FE	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	6236	6236	6236	6236	6236
Adjusted R-squared	0.3480	0.2040	0.3035	0.2534	0.4989

With regard to the baseline results for Equation (4), regarding the analysis by bank size, in the first two columns of Table 5, the significant and negative coefficient on $fintech_{i,t}$ in Column 1 suggests that FinTech adoption has negative effects on liquidity creation for large banks and not for small banks. As regards the results on the impact of the COVID-19 pandemic in the last two columns in Table 5, the coefficient on the interaction term is also significant and negative for large and small banks indicating that irrespective of size, banks that had higher levels of FinTech adoption created less liquidity during this pandemic period.

5. Controlling for endogeneity

5.1. Propensity score matching

We first employ PSM to mitigate the concern that non-random adoption of FinTech may affect banks' liquidity creation. We use the PSM method to match high FinTech adoption banks[10] to eliminate the concern that the sample selection is not random and address the common trend assumption under the baseline model. The banks' FinTech adoption variables in this study are constructed from news article; however, large banks receive more attention from media institutions than small banks. Hence, large banks may have more news exposure than small banks and not all the banks are willing to expose their FinTech investment. Therefore, we apply a PSM method to mitigate this potential self-selection bias. We use the radius method to randomly select the PSM sample within the 0.05 range and

[10] High FinTech adoption banks refers to those banks whose FinTech index is higher than the medium FinTech index of all banks at time t.

Table 3
Effect of FinTech adoption on liquidity creation: Mediating role of the COVID-19
This table reports the results of equation (5) estimated using ordinary least squares techniques. The main dependent variable is the liquidity creation variables which are measured following Berger and Bouwman (2009). We specifically test five liquidity creation categories in the regression models, namely, total, on-balance sheet, off-balance sheet, asset-side and liability-side liquidity creation. The independent variable *fintech* is FinTech adoption variable for individual BHC level. A higher value of *fintech* indicates that the BHC has higher FinTech adoption. The *gc_covid* is the growth rate of cumulative confirmed cases of the COVID-19 pandemic. The *fintech* × *gc_covid* is the interaction term of *fintech* and *gc_covid*. The sample encompasses 6236 bank-quarter observations of 300 US listed BHCs from the first quarter of 2015 to the second quarter of 2021. This regression model includes year-quarter and BHC level fixed effect. Appendix A includes the definitions of all variables. *, **, *** represents significance at 10%, 5% and 1% level, respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)
	lc_total	*lc_on*	*lc_off*	*lc_asset*	*lc_lia*
fintech	−0.0084***	−0.0023	−0.0027	−0.0017	−0.0008
	(-2.6030)	(-0.8601)	(-0.9281)	(-0.7134)	(-0.4147)
gc_covid	0.0089	0.0030	0.0056*	0.0023	0.0003
	(1.5814)	(0.6486)	(1.8156)	(0.5043)	(0.1563)
fintech × *gc_covid*	−0.0116***	−0.0119***	−0.0008	−0.0124***	0.0018
	(-3.9249)	(-4.1951)	(-0.5490)	(-3.4823)	(1.1223)
cr	0.3571***	0.1318***	0.1988***	0.1300***	0.0058
	(5.3455)	(5.8966)	(4.0209)	(6.0612)	(0.9136)
zs	−0.0047	0.0002	−0.0047**	−0.0009	0.0008
	(-1.4368)	(0.0683)	(-2.3367)	(-0.3700)	(0.6900)
ev	−0.0219***	−0.0280***	0.0049	−0.0203**	−0.0067
	(-2.6044)	(-3.4268)	(0.8663)	(-2.1479)	(-1.1596)
roa	0.0231***	0.0025	0.0187***	0.0074	−0.0027
	(2.9479)	(0.4813)	(2.8029)	(1.5462)	(-0.9808)
bs	−0.0276*	−0.0164	−0.0134	0.0033	−0.0203***
	(-1.9152)	(-1.0598)	(-1.3201)	(0.1995)	(-3.3610)
capr	0.0157	−0.2455	0.2297*	0.4724**	−0.7359***
	(0.0895)	(-1.3525)	(1.8290)	(2.4194)	(-7.9668)
Constant	0.5904**	0.5151**	0.1345	−0.1082	0.6294***
	(2.3893)	(2.2008)	(0.7746)	(-0.4377)	(6.4422)
Bank FE	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	6236	6236	6236	6236	6236
Adjusted R-squared	0.3495	0.2064	0.3039	0.2561	0.4989

select six bank-level variables for analysis using the PSM method: credit risk (*cr*), z-score (*zs*), earnings volatility (*ev*), profitability (*roa*), bank size (*bs*) and capital ratio (*capr*). The treated group is assigned when banks' FinTech adoption variable is higher than the median number of FinTech adoption across all samples in a given year. As shown in Table 6, the results remain quantitatively unchanged from the baseline results in Table 2. We include the matching results of the PSM in Appendix C. The table shows that the t-statistics of the matched sample are insignificant. This suggests that these control variables are suitable for the PSM method.

5.2. System generalised method of moments

We next apply the system GMM estimation technique to tackle the endogeneity issue and account for the dynamic properties of our panel. The method was introduced by Arellano and Bond (1991), and further developed by Arellano and Bover (1995) and Blundell and Bond (1998). In this approach, the treatment of all explanatory variables as endogenous is facilitated by orthogonal utilization their respective past values as instrumental variables. Additionally, a matching equation is established, incorporating the first differences of all the variables. The model is estimated through the GMM, in which the lagged values of the right-hand side variables are employed.[11] The implementation of first differencing effectively eliminates unobserved heterogeneity and mitigates the possibility of omitted variable bias. The fact that bank FinTech adoption and liquidity creation tend to be interrelated over time prescribes the use of a dynamic model. Thus, the system GMM has better finite sample properties in terms of bias and root mean squared error than those of the difference GMM because of the use of a system of two equations in level and first difference. However, the two-step estimates of the standard errors tend to be downward biased (Blundell & Bond, 1998). Hence, we follow Windmeijer's (2005) approach for finite sample correction when reporting standard errors.

Table 7 presents the results of the GMM method. The results of independent variable $fintech_{i,t}$ are statistically significant and negative in Columns 1, 2 and 4, suggesting that banks' FinTech adoption is negatively correlated with their liquidity creation. The results are consistent with our baseline results, which increases the robustness of our argument that banks' FinTech adoption reduces their liquidity creation, except for the results in Columns 3 and 5. We further report the Hansen test of overidentifying restriction, in which the null hypothesis is that the instruments used are appropriate. The statistical result implies that the instruments are valid in the

[11] We use 'xtabond2' command in Stata to conduct the system GMM approach. Roodman (2009) provides more detail of the estimation procedure.

Table 4
Effect of sub-categories of FinTech on liquidity creation
Panel A of this table reports the results of equation (4) by sub-categories of FinTech adoption. Panel B presents the results of equation (5) with the interaction terms between different categories of FinTech adoption and the growth rate of cumulative confirmed cases of the COVID-19 pandemic included. The main dependent variable is the total liquidity creation, *lc_total*. Independent variables represent each sub-category of FinTech types, including AI, blockchain, cloud and internet. The interaction terms are linked with banks' each FinTech type and *gc_covid*. This regression model includes year-quarter and BHC level fixed effect. Appendix A includes the definitions of all variables. *, **, *** represents significance at 10%, 5% and 1% level, respectively.

Panel A: Results for sub-categories FinTech adoption

VARIABLES	(1)	(2)	(3)	(4)
	lc_total	*lc_total*	*lc_total*	*lc_total*
ai	−0.0267			
	(-1.5177)			
blockchain		−0.0047		
		(-0.6941)		
cloud			−0.0141*	
			(-1.9517)	
internet				−0.0136**
				(-2.3609)
Constant	0.5557**	0.5441**	0.5492**	0.5608**
	(2.2375)	(2.1807)	(2.2046)	(2.2536)
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Observations	6236	6236	6236	6236
Adjusted R-squared	0.3475	0.3467	0.3470	0.3474

Panel B: Mediating effect of the COVID-19 pandemic – sub-categories of FinTech

VARIABLES	(1)	(2)	(3)	(4)
	lc_total	lc_total	lc_total	lc_total
ai	−0.0208			
	(-1.0886)			
ai × *gc_covid*	−0.0214**			
	(-2.3388)			
blockchain		−0.0038		
		(-0.5542)		
blockchain × *gc_covid*		−0.0204*		
		(-1.8329)		
cloud			−0.0081	
			(-0.6521)	
cloud × *gc_covid*			−0.0076	
			(-0.9493)	
internet				−0.0063
				(-1.0596)
internet × *gc_covid*				−0.0178***
				(-2.7474)
Constant	0.5676**	0.5633**	0.5579**	0.5789**
	(2.2949)	(2.2726)	(2.2501)	(2.3447)
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.3480	0.3477	0.3473	0.3489

model.

5.3. The effect of the CCPA policy on bank liquidity creation

In this section, we explore the effects of the CCPA[12] on bank liquidity creation. In general, the CCPA enhanced Californian residents' personal data privacy in the first quarter of 2020. For instance, the CCPA gives Californian residents the authority to require businesses to delete their personal information and not sell their personal data. Given that FinTech applications require substantial personal data of customers for analysis, we argue that the introduction of the CCPA has reduced FinTech banks' analytical ability owing to the lack of accessibility to customer information. Moreover, the CCPA limits the sharing behaviours between FinTech firms and banks, which lowers the probability of these financial institutions sharing customer information with other institutions. Therefore,

[12] For more details, see https://oag.ca.gov/privacy/ccpa.

Table 5
Effect of FinTech adoption on liquidity creation: Subsample analysis by bank size
This table reports the results of equations (4) and (5) estimated using ordinary least squares techniques with interaction terms in this study. The main dependent variable is the liquidity creation variables which are measured following Berger and Bouwman (2009). This table only includes the total liquidity creation as the main dependent variable. The independent variable is *fintech* is FinTech adoption variable for individual BHC levels. A higher value of *fintech* indicates that the BHC has higher FinTech adoption. The *gc_covid* is the growth rate of cumulative confirmed cases of the COVID-19 pandemic. Large banks' GTA are more than $3 billion, and small banks' GTA are lower than $3 billion. The interaction terms are linked with banks' FinTech adoption and *gc_covid*. The sample encompasses 6236 bank-quarter observations of 300 US listed BHCs from the first quarter of 2015 to the second quarter of 2021. This regression model includes year-quarter and BHC level fixed effect. Appendix A includes the definitions of all variables. *, **, *** represents significance at 10%, 5% and 1% level, respectively.

	Dependent variable: *lc_total*			
VARIABLES	(1)	(2)	(3)	(4)
	Large BHCs	Small BHCs	Large BHCs	Small BHCs
fintech	−0.0088**	−0.0087	−0.0065**	0.0300**
	(-2.5587)	(-0.2154)	(-2.0064)	(2.3042)
gc_covid			0.0070	−0.0072
			(1.2288)	(-0.2993)
fintech × *gc_covid*			−0.0091***	−0.0753***
			(-3.7217)	(-9.1174)
Constant	0.7118**	0.5004	0.7394**	0.5545
	(2.3405)	(1.0669)	(2.4395)	(1.1845)
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Observations	4350	1886	4350	1886
Adjusted R-squared	0.3790	0.3760	0.3801	0.3845

Table 6
Effect of FinTech adoption on bank liquidity creation (using PSM)
This table reports the results of equation (4) estimated using ordinary least squares techniques after PSM in this study. The treated banks are the banks with high FinTech adoption, measured by whether the banks' FinTech index is higher than the medium FinTech at time *t*. We use the radius method to randomly select the PSM sample within the 0.05 range and select six bank-level variables for analysis using the PSM method: credit risk (*cr*), z-score (*zs*), earnings volatility (*ev*), profitability (*roa*) and capital ratio (*capr*). The main dependent variable is the liquidity creation variables which are measured following Berger and Bouwman (2009). The independent variable is *fintech* is FinTech adoption variable for individual BHC levels. A higher value of *fintech* indicates that the BHC has higher FinTech adoption. The sample encompasses 6236 bank-quarter observations of 300 US listed BHCs from the first quarter of 2015 to the second quarter of 2021. This regression model includes year-quarter and BHC level fixed effect. Appendix A includes the definitions of all variables. *, **, *** represents significance at 10%, 5% and 1% level, respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)
	lc_total	*lc_on*	*lc_off*	*lc_asset*	*lc_lia*
fintech	−0.0083**	−0.0054**	0.0001	−0.0048*	−0.0003
	(-2.4214)	(-1.9863)	(0.0493)	(-1.7667)	(-0.1523)
cr	0.4015***	0.1150***	0.2471***	0.1192***	0.0016
	(4.5237)	(4.8859)	(3.6764)	(5.3015)	(0.2126)
zs	−0.0040	0.0033	−0.0066**	0.0006	0.0023
	(-0.9178)	(1.1574)	(-2.3505)	(0.2135)	(1.5784)
ev	−0.0183*	−0.0319***	0.0120*	−0.0244**	−0.0065
	(-1.8113)	(-3.2804)	(1.7087)	(-2.3083)	(-0.9742)
roa	0.0274**	−0.0013	0.0252***	0.0066	−0.0044
	(2.4546)	(-0.2118)	(3.0015)	(1.1295)	(-1.4210)
bs	−0.0422**	−0.0464***	0.0018	−0.0229*	−0.0243***
	(-2.5425)	(-3.6845)	(0.2001)	(-1.8603)	(-3.2425)
capr	0.3454	0.0990	0.2059	0.9264***	−0.8619***
	(1.4721)	(0.5230)	(1.3563)	(5.1945)	(-7.3065)
Constant	0.8017***	1.0102***	−0.1368	0.2954	0.7271***
	(2.6647)	(4.9783)	(-0.7531)	(1.5148)	(5.8163)
Bank FE	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	4374	4374	4374	4374	4374
Adjusted R-squared	0.3719	0.1744	0.3483	0.3067	0.5303

we consider a dummy variable that indicates the period after the first quarter of 2020 as the post period (*post*) in the DiD setting. We also include banks operating in California in the treatment group (*treat*) and banks not operating in California in the control group. In the DiD regression model, we include bank and year-quarter fixed effects and control variables. The DiD model is as follows:

Table 7
Effect of FinTech adoption on bank liquidity creation (using system GMM)
This table reports the estimation results GMM panel estimator as introduced by Arellano and Bond (1991), Arellano and Bover (1995), and Blundell and Bond (1998). The null hypothesis of the Hansen test is the instruments used are not associated with residuals (over-identifying restrictions). The main dependent variable is the liquidity creation variables which are measured following Berger and Bouwman (2009). The lc_total_{t-1}, lc_on_{t-1}, lc_off_{t-1}, lc_asset_{t-1} and lc_lia_{t-1} are lagged variable of the dependent variables in GMM estimator. The independent variable *fintech* is FinTech adoption variable for individual BHC level. A higher value of *fintech* indicates that the BHC has higher FinTech adoption. The sample encompasses 6236 bank-quarter observations of 300 US listed BHCs from the first quarter of 2015 to the second quarter of 2021. This regression model includes year-quarter and BHC level fixed effect. Appendix A includes the definitions of all variables. *, **, *** represents significance at 10%, 5% and 1% level, respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)
	lc_total	lc_on	lc_off	lc_asset	lc_lia
fintech	−0.0788***	−0.0266***	0.0289**	−0.0166***	−0.0033**
	(-3.9236)	(-3.6373)	(2.5042)	(-2.7638)	(-2.3915)
lc_total_{t-1}	0.3919***				
	(3.1778)				
lc_on_{t-1}		0.8277***			
		(26.4111)			
lc_off_{t-1}			−0.0534		
			(-0.6121)		
lc_asset_{t-1}				0.8099***	
				(24.7224)	
lc_lia_{t-1}					0.9622***
					(102.1195)
Constant	−0.1630**	0.0425**	−0.2937***	−0.0208	0.0190***
	(-2.0278)	(2.4513)	(-3.7851)	(-1.2067)	(3.7538)
Controls	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	5934	5934	5934	5934	5934
Hansen test (p value)	0.982	0.992	0.948	0.960	0.991

$$liquidity\_creation_{i,t} = \beta_0 + \beta_1 post_t + \beta_2 treat_i + \beta_3 post_t \times treat_i + \vartheta' bank_{controls} + \gamma_i + \delta_t + \varepsilon_{i,t} \tag{6}$$

The main variable of interest is the interaction term, $post \times treat$, which represents the change in liquidity creation for the treatment group of banks relative to the change for the control group of banks after the CCPA came into effect. Table 8 reports the results of the DiD regression model. Panel A presents the regression results of the full sample. We find that the coefficients on *post* across the columns are all significant and positively associated with bank liquidity creation, which suggests that banks created more liquidity after the CCPA became effective. Furthermore, we find that *treat* has a significant and negative relationship with $lc\_asset_{i,t}$ as shown in Column 4, while the banks in the treatment group have a significant and positive impact on $lc\_total_{i,t}$, $lc\_off_{i,t}$ and $lc\_lia_{i,t}$ as shown in Columns 1, 3 and 5, respectively. The results suggest that the treatment group had less liquidity creation in asset-side activities and higher total, off-balance sheet and liability-side activities than the control banks. Importantly, the coefficient on the interaction term $treat \times post$ in Columns 1, 2 and 4, is significant and negative for $lc\_total_{i,t}$, $lc\_on_{i,t}$ and $lc\_asset_{i,t}$, respectively. The findings indicate that the banks operating in California created less liquidity than the banks outside California after the enactment of the CCPA in the first quarter of 2020.

Panel B presents the results for the PSM sample. The PSM matched sample is similar to the one used in the PSM match analysis in Section 5.1. The PSM sample is built using the same process as the PSM examination for baseline model, as shown in Section 5.1. The results are consistent with those for the full sample. The interaction term, $treat \times post$ in Columns 1, 2 and 4 is significantly and negatively associated with $lc\_total_{i,t}$, $lc\_on_{i,t}$ and $lc\_asset_{i,t}$. The results are consistent with those for the full sample, namely, that banks operating in California created less liquidity than non-Californian banks after the CCPA came into effect.

We conduct diagnostic tests to examine the parallel trends assumption and confirm the authenticity of the CCPA by employing placebo tests. First, we use the parallel trends assumption by analysing data for four quarters before and after the event as *pre4* and *post4* samples, respectively. Next, we interact these time dummies with the *treat* banks. As reported in Column 1 of Panel C in Table 8, the coefficient on the interaction term $pre \times treat$ is insignificant across all variables and turns significant and negative for $post1 \times treat$ and $post3 \times treat$. In the first placebo test, we randomly assign the second quarter of 2017 as a pseudo CCPA effective time. Column 2 of Panel C reports that there is no significant coefficient on the interaction term $post \times treat$. Furthermore, Fig. 3 shows the results of the second placebo test in which we randomly select 50% of the *treat* banks and repeat the process 500 times. As the figure shows, the distribution of the coefficients on the interaction term matches the normal distribution because the coefficient line of the interaction term is far away from the zero point.

6. Robustness check

We use bank *i*'s FinTech index at time *t* divided by the total news of bank *i* at time *t* as an alternative measurement of the FinTech

Table 8

Effect of CCPA on bank liquidity creation

This table reports the DiD estimation of equation (6). The liquidity creation variables are measured following Berger and Bouwman (2009). *post* is dummy variable representing the date after 2020 quarter 1 as an indicator for the enactment of CCPA. The *treat* represents California as treatment state, and the control group is the other states in the US. Panel A reports the results of the full sample. Panel B reports the results of PSM results, where the PSM is radius in 0.05 range. This regression model includes year-quarter and BHC level fixed effects. Appendix A includes the definitions of all variables. *, **, *** represents significance at 10%, 5% and 1% level, respectively.

Panel A: Regression results of DiD model, Full sample

VARIABLES	(1)	(2)	(3)	(4)	(5)
	lc_total	*lc_on*	*lc_off*	*lc_asset*	*lc_lia*
post	0.3516***	0.2287***	0.1113***	0.1770***	0.0495***
	(6.4834)	(5.2372)	(3.8251)	(4.1602)	(3.1367)
treat	0.1414***	0.0160	0.1467***	−0.1725***	0.1922***
	(3.4189)	(0.4386)	(5.8771)	(-4.7005)	(11.5724)
post × *treat*	−0.0182***	−0.0184***	0.0005	−0.0167***	−0.0033
	(-2.7502)	(-2.9265)	(0.2119)	(-2.7321)	(-1.2153)
Constant	0.4732***	0.4147***	0.1184**	−0.1302*	0.5523***
	(5.0155)	(5.3983)	(2.0388)	(-1.6464)	(16.5702)
Controls	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	6236	6236	6236	6236	6236
Adjusted R-squared	0.9265	0.9313	0.8415	0.9188	0.9602

Panel B: The effect of CCPA on banks' liquidity creation, PSM sample

VARIABLES	(1)	(2)	(3)	(4)	(5)
	lc_total	lc_on	lc_off	lc_asset	lc_lia
post	0.0917***	0.0644***	0.0284***	−0.0001	0.0653***
	(11.4058)	(9.1863)	(7.1291)	(-0.0202)	(22.5409)
treat	0.1560***	0.0317	0.1458***	−0.1578***	0.1931***
	(3.7353)	(0.8635)	(5.7624)	(-4.2454)	(11.5421)
post × *treat*	−0.0178***	−0.0179***	0.0006	−0.0165***	−0.0031
	(-2.6883)	(-2.8558)	(0.2257)	(-2.6998)	(-1.1251)
Constant	0.5023***	0.4494***	0.1140*	−0.0975	0.5539***
	(5.2602)	(5.7844)	(1.9323)	(-1.2165)	(16.4765)
Controls	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Year-quarter	Yes	Yes	Yes	Yes	Yes
Observations	6100	6100	6100	6100	6100
Adjusted R-squared	0.9259	0.9313	0.8406	0.9194	0.9593

Panel C: Robustness checks, parallel trends, and placebo test with random event time

VARIABLES	(1)	(2)
	lc_total	lc_total
pre4 × *treat*	0.0076	
	(0.6950)	
pre3 × *treat*	−0.0095	
	(-0.8849)	
pre1 × *treat*	−0.0200	
	(-1.5580)	
Current	−0.0069	
	(-0.4172)	
post × *treat*		−0.0025
		(0.0040)
treat		0.1414***
		(0.0413)
post		0.3494***
		(0.0543)
post1 × *treat*	−0.0211*	
	(-1.7130)	
post2 × *treat*	−0.0135	
	(-0.9861)	
post3 × *treat*	−0.0271**	
	(-2.3795)	
post4 × *treat*	−0.0251	
	(-1.5803)	
Constant	2.3121***	0.4795***

(*continued on next page*)

Table 8 (*continued*)

Panel C: Robustness checks, parallel trends, and placebo test with random event time		
VARIABLES	(1)	(2)
	lc_total	lc_total
	(4.9665)	(0.0947)
Control	Yes	Yes
Bank FE	Yes	Yes
Year-quarter FE	Yes	Yes
Observations	1684	6236
Adjusted R-squared	0.9022	0.9264

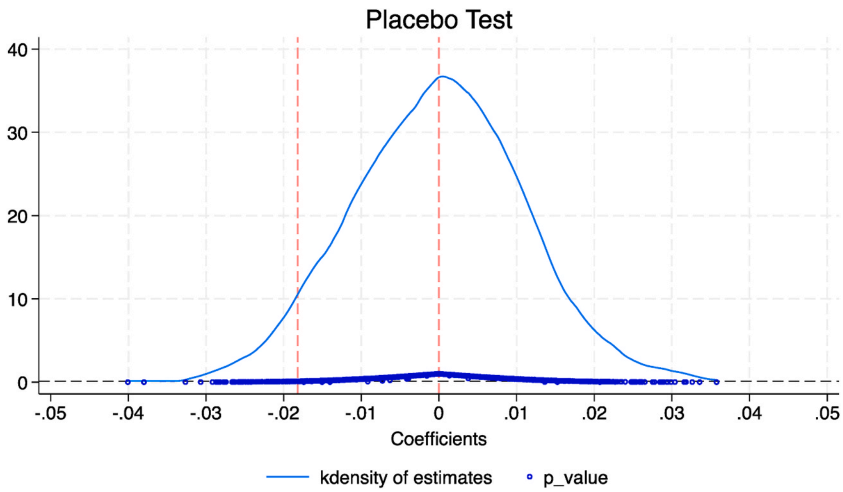

Fig. 3. Placebo test, random treatment banks.

Table 9
Alternative measurement for FinTech index
This table reports the results of equation (4) estimated using ordinary least squares techniques. The main dependent variable is the liquidity creation variables which are measured following Berger and Bouwman (2009). We specifically test five liquidity creation categories in the regression models, namely, total, on-balance sheet, off-balance sheet, asset-side and liability-side liquidity creation. Independent variables *fint_ratio* is calculated by the ratio of bank *i*'s total FinTech news at time *t* to the bank's total news at time *t*. The sample encompasses 6236 bank-quarter observations of 300 US listed BHCs from the first quarter of 2015 to the second quarter of 2021. This regression model includes year-quarter and BHC level fixed effect. Appendix A includes the definitions of all variables. *, **, *** represents significance at 10%, 5% and 1% level, respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)
	lc_total	*lc_on*	*lc_off*	*lc_asset*	*lc_lia*
fint_ratio	−0.0501**	−0.0223*	−0.0093	−0.0287**	0.0049
	(-6.6084)	(-5.4197)	(-3.6563)	(-4.2639)	(-4.3564)
Constant	−12.4886***	−9.3418***	−3.0016***	−6.2965***	−2.9474***
	(-6.9844)	(-6.1192)	(-3.2642)	(-4.1770)	(-5.1199)
Controls	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	6236	6236	6236	6236	6236
Adjusted R-squared	0.3474	0.2037	0.3033	0.2534	0.4989

index. The data of banks' news are collected from the Refinitiv Workspace database. Table 9 reports the results of the alternative measurement of FinTech news to total news of banks. The results indicate that banks' total, on-balance, and asset-side liquidity creation is statistically significant and negatively correlated with the alternative variable. This furthers the robustness of the results from our baseline model and strengthens our argument.

7. Conclusion

In the past decade, the rise of the FinTech industry and increasing use of its applications in the banking sector have played a prominent role in financial markets and drawn academic attention to this area. Nevertheless, the recent literature has focused on the external impact of the FinTech industry on the banking sector or the relationship between banks' FinTech development and their performance (e.g., credit risk and failure risk) and, specifically, on banks in China. Thus, the effect of banks' FinTech adoption on their liquidity creation remains unclear and the effects on the US banking sector are unexplored in the existing empirical literature.

To address this gap in the literature, we used data on a sample of the top 300 BHCs in the US using a quarterly frequency time frame from Q1 2015 to Q2 2021. Further, we constructed FinTech indexes to measure the BHCs' FinTech development level in each quarter by using data from Refinitiv Workspace to examine the effects of BHCs' FinTech development on their liquidity creation. We presented five major findings as follows. First, we found that BHCs that had better FinTech adoption created less liquidity in terms of total, on-balance sheet, and asset-side liquidity. Second, BHCs that had a high level of FinTech development created less liquidity during the COVID-19 pandemic period, and the pandemic had significant effects on the total, on-balance sheet, and asset-side liquidity creation. Further, these results for the baseline model held on using an alternative measurement approach. Third, we found that the effect of FinTech on liquidity creation differed according to FinTech type. For example, the adoption of cloud and internet caused BHCs to create less liquidity in the entire sample period whereas the effects differed during the COVID-19 pandemic period. We found that BHCs' AI, blockchain and internet adoption reduced their liquidity creation. Fourth, we found that only large BHCs that had enhanced FinTech adoption created less total liquidity during the entire sample period but large and small BHCs that had better FinTech adoption created less liquidity during this pandemic period.

The empirical results of this study have important implications for bank managers, investors and regulators. First, we found that banks that had better FinTech development created less liquidity, suggesting that bank managers should invest in, or cooperate with, FinTech firms to obtain appropriate technologies to reduce their liquidity creation to prevent external shock because liquidity creation involves risk-taking activities. For example, the adoption of cloud and internet FinTech applications decreases banks' liquidity creation. Moreover, prior studies have found that banks' liquidity creation is associated with risky activities, which expose banks to illiquidity risk from, for instance, sudden and large withdrawals or fire sales (Allen & Gale, 2004; Allen & Santomero, 1997; Diamond & Dybvig, 1983; Diamond & Rajan, 2011). The results indicate that the adoption of FinTech reduces banks' liquidity creation during a financial crisis period (e.g., the COVID-19 pandemic). This result can assist bank managers in decision-making about whether they should adopt FinTech, such as cloud and internet, to reduce the probability of exposure to the risk of failure because of a financial crisis by filtering out long-term low credit quality borrowers. Second, the results have important implications for investors' decision-making about their investment portfolios. Specifically, investors can invest in banks that have enhanced FinTech adoption because these banks create less liquidity and thus have less risky assets. Third, this study is important for regulators to consider whether they should draft policies to promote and encourage the development of FinTech in the banking sector. This can help banks to reduce their liquidity creation by absorbing high-quality borrowers, mitigating potential risk exposures and addressing systemic shocks from crises.

Nevertheless, this study has the following limitations that future researchers need to address. First, we used a news count to identify the FinTech development of banks; however, this method is not very accurate in measuring the true FinTech development. Future studies can use banks' official disclosures to evaluate their FinTech adoption (e.g., 10-K forms). Second, we did not include the effect of various types of FinTech firms on banks' liquidity creation. For instance, FinTech firms can be regarded as competitors to banks or be in a cooperative relationship. As competitors, FinTech firms could take a share of the funding market from banks (e.g., through P2P and crowdfunding), which could reduce banks' liquidity creation. However, cooperation with FinTech firms could increase banks' willingness to adopt FinTech. Therefore, future studies can consider the effect of various types of FinTech firms on banks' liquidity creation. Third, we only covered the financial crisis caused by the COVID-19 pandemic. Future studies could examine the relationship between banks' FinTech adoption and other financial crises (e.g., the 2008 global financial crisis).

Declarations of competing interest

None.

Data availability

Data will be made available on request.

Acknowledgement

We express our gratitude to discussants Yueteng Zhu and Noah Urban at the Chinese International Risk Forum in 2022 and the Financial Management Association in 2023, respectively. We also thanks participants at the colloquium/conference at Curtin University in 2021 and the 12th Financial Engineering and Banking Society in 2023, for their valuable comments and suggestions.

Appendix A. Definition of variables

Variable	Definition
liquidity creation variables	[source: Berger and Bouwman (2009) and Federal Reserve of Chicago database]
lc_total	BHC's total liquidity creation. Including both on-balance sheet and off-balance sheet activities. The variable is calculated by total liquidity creation divided by gross total assets (GTA). The detail of the calculation and items are included in Equation (1) and Appendix B.
lc_on	On balance sheet activities. Including on balances sheet activities only. It is combined by asset side and liabilities side activities. The variable is calculated by on balance sheet liquidity creation divided by gross total assets (GTA). The detail of the calculation and items are included in Equation (1) and Appendix B.
lc_off	Off balances sheet activities. Including off balances sheet activities only. The variable is calculated by off balance sheet liquidity creation divided by GTA. The detail of the calculation and items are included in Equation (1) and Appendix B.
lc_asset	Asset side liquidity creation. Including asset-side activities only. The variable is calculated by asset-side sheet liquidity creation divided by GTA. The detail of the calculation and items are included in Equation (1) and Appendix B.
lc_lia	Liabilities side liquidity creation. Including liabilities-side activities only. The variable is calculated by liabilities-side sheet liquidity creation divided by GTA. The detail of the calculation and items are included in Equation (1) and Appendix B.
FinTech variables	[source: Refinitiv Workspace]
fintech	BHC *i*'s overall FinTech adoption index at time *t*. Measured by nature logarithm of BHC *i*'s all the FinTech news at time *t*.
ai	BHC *i*'s AI adoption index at time *t*. Measured by nature logarithm of BHC *i*'s AI news at time *t*.
blockchain	BHC *i*'s blockchain adoption index at time *t*. Measured by nature logarithm of BHC i's blockchain news at time *t*.
cloud	BHC *i*'s cloud adoption index at time *t*. Measured by nature logarithm of BHC *i*'s cloud news at time *t*.
internet	BHC *i*'s internet adoption index at time *t*. Measured by nature logarithm of BHC *i*'s internet news at time *t*.
fint_ratio	The ratio of banks' FinTech news and their news. It is calculated by using bank *i*'s total FinTech news at time *t* divided by bank *i*'s total news at time *t*.
Controls - BHCs level	[source: Federal Reserve of Chicago database]
cr	Credit risk which is measured as the BHCs' Basel I risk-weighted assets and off-balance sheet activities divided by GTA.
zs	Z-score which is calculated as a BHCs' return on assets plus the equity capital/GTA ratio divided by the standard deviation of the return on assets.
ev	Earning volatility, it is measured by the standard deviation of the bank's return on assets over the previous twelve (minimum: eight) quarters.
roa	Return on asset which is measured as the ratio of net income to total assets.
bs	Bank size which is calculated as the natural logarithm of gross total asset.
capr	Capital ratio which is measured as the ratio of equity to total asset.
COVID-19 variables	[source: John Hopkins COVID-19 database]
gc_covid	The growth rate of COVID-19 cases of the state *j* that BHC *i* operates at time *t*.

Appendix B. Liquidity creation measurement (Berger & Bouwman, 2009)

Assets		
Illiquid assets (+0.5) Commercial real estate loans (CRE) Loans to finance agricultural production Commercial and industrial loans (C&I) Other loans and lease financing receivables Other real estate (OREO) Customers' liability on bankers' acceptances Investment in unconsolidated subsidiaries Intangible assets Premises Other assets	Semiliquid assets (0) Residential real estate loans (RRE) Consumer loans Loans to depository institutions Loans to state and local governments Loans to foreign governments	Liquid assets (−0.5) Cash and due from other institutions All securities (regardless of maturity) Trading assets Federal funds sold
Liabilities plus equity Liquid liabilities (+0.5)	Semiliquid liabilities (0)	Illiquid liabilities plus equity (−0.5)
Transactions deposits Saving deposits Overnight federal funds purchased Trading liabilities	Time deposits Other borrowed money	Bank's liability on bankers acceptances Subordinated debt Other liabilities Equity
Off-balance sheet guarantees Liquid guarantees (+0.5)	Semiliquid guarantees (0)	Illiquid guarantees (−0.5)
Unused commitments Net standby letters of credit Commercial and similar letters of credit All other off-balance sheet liabilities	Net credit derivatives Net securities lent	Net participations acquired

(continued on next page)

(*continued*)

Assets		
Off-balance sheet derivatives		
		Liquid derivatives (−0.5)
		Interest rate derivatives
		Foreign exchange derivatives
		Equity and commodity derivatives

Appendix C. PSM

This table reports the comparisons of the matching criteria between PSM treated and control banks. The treated group is assigned when banks' FinTech adoption variable is higher than the medium number of FinTech adoption across all sample in a given year. We use the radius method to randomly select the PSM sample within the 0.05 range and select six bank-level variables for analysis using the PSM method: credit risk (*cr*), z-score (*zs*), earnings volatility (*ev*), profitability (*roa*), bank size (*bs*) and capital ratio (*capr*). *, **, *** represents significance at 10%, 5% and 1% level, respectively.

VARIABLES	Prematched			Matched		
	Treated	Control	t-stat	Treated	Control	t-stat
cr	0.8249	0.8489	−2.32**	0.8327	0.8392	−0.33
zs	2.1627	2.1744	−0.19	2.1266	2.018	1.44
ev	0.3811	0.3437	3.30***	0.3831	0.3620	1.14
roa	0.6810	0.5981	3.93***	0.6716	0.6295	1.42
bs	19.51	15.709	46.95***	19.376	19.308	0.51
capr	0.10843	0.1150	−4.65***	0.1095	0.1091	0.69

Appendix D. FinTech related news examples

BHC ticker	Date	News title and source	Main text (first sentence)
WFC	11/Feb/2017	REFILE-Wells Fargo sets up artificial intelligence team in tech push - Reuters News	Wells Fargo & Co has created a team to develop artificial intelligence-based technology and appointed a lead for its newly combined payments businesses, as part of an ongoing push to strengthen its digital offerings …
BAC	08/Sep/2021	US Patent Issued to Bank of America on Sept. 7 for "Blockchain management platform for performing asset adjustment, cross sectional editing, and bonding" (Colorado, Texas Inventors) - US Federal News	According to the abstract, released by the US Patent & Trademark Office: "Embodiments of the present invention provide a system for expediting validation and authorization of transactions between end points …"
C	15/Mar/2017	Cloud security vendor raises $12 million - American Banker (USA)	The venture capital firms of Goldman Sachs and Citigroup, along with the fund backed by Google's chairman, have invested in a vendor that helps banks secure their cloud technology …

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