The dark side of bank digitalization: Bank liquidity creation and digital transformation costs*

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Abstract

The digitalization of financial services, including that of commercial banks, has seen a rapid proliferation in the recent years. We therefore examine how digital transformation can affect liquidity creation using a novel setting that exploits Indonesia's unique regulatory environment, which only allows the establishment of new digital banks through mergers and acquisitions. Our results document the negative impact of digital transformation on bank liquidity creation within small-sized banks. These findings are driven by the high cost associated with digital infrastructure and digital banks' inability to achieve economies of scale due to their small business size, leading to higher business costs and lower operating efficiency. This evidence offers novel insights into the potential adverse effect of digital transformation in the banking sector.

JEL-Codes: G21, G34, O33.
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1 Introduction

The incorporation of digital technology into traditional banking business model has led to the proliferation of digital banks. Unlike traditional banks that primarily rely on brick-and-mortar outlets, digital banks offer services only via electronic means such as web applications, telephone, and online chat. Theories suggest a positive relation between technological innovation and bank competitiveness because the former helps banks enhance monitoring and increase efficiency (Boot and Thakor, 2000; Diamond, 1984; Thakor, 2020), which ultimately improves financial intermediary functions (Schelling and Towbin, 2022). Digital innovation also helps banks design tailor-made products to gain market share and capture the untapped market, leading to higher liquidity creation (Buchak et al., 2018; Fuster et al., 2019). Nevertheless, the beginning phase of digital innovation necessitates high fixed costs of initial investments and a learning period to understand the new technology (Saka et al., 2022). This requires banks to exploit economies of scale by amortizing these costs over a large customer base (Feyen et al., 2021).

While a rapidly growing literature has studied the impact of digital innovation on credit expansion within FinTechs (Allen et al., 2022; Bao and Huang, 2021), research that specifically focuses on the banking sector is still scarce. Given this gap in the literature, we aim to examine the effect of digital transformation on bank liquidity creation. Unfortunately, quantifying such an effect is notoriously challenging due to the endogenous relationship between digital transformation and liquidity creation, as well as the difficulty in establishing counterfactuals (Bollaert et al., 2021).

To tackle this issue, we exploit Indonesia's unique banking sector's regulatory environment to generate a plausibly exogenous variation in digital transformation status. Indonesian financial authorities actively aim to restructure and consolidate the industry by placing a regulatory barrier that significantly increases the cost of establishing new banks while encouraging mergers and acquisitions (M&As) of smaller banks (Poczter, 2016; Shaban and James, 2018). Consequently, no new banks have been established since the 1997 Asian Financial Crisis, and digital banks can only be established via acquiring existing banks (we refer to this as digital acquisition or digital transformation). This situation causes the bank M&A process in Indonesia to be unpredictable and quick.[1] Literature suggests that M&As in the banking sector is plausibly exogenous if they are driven by strong regulatory and structural forces that are not intended for shareholder value maximization (Berger et al., 1999; Chen and Vashishtha, 2017; Liebersohn, 2024; Pilloff, 2004). These acquisition characteristics allow us to use staggered difference-in-differences (DID) estimation to exploit bank variation over time in establishing new digital banks and compare how the treatment group (digital banks) responds to its new business model relative to a control group (traditional banks).

Using quarterly data of Indonesian banks between 2014 and 2022, we find that digital transformation decreases liquidity creation by 14.1 percentage points. This reduction in liquidity creation also leads to a decline in digital banks' market share relative to traditional banks. When we decompose liquidity creation into asset-side, liability-side, and off-balance sheet dimensions, we find that the asset-side drives digital banks' overall liquidity creation

[1] Many small- and medium-sized banks in Indonesia have similar business characteristics and performance. Therefore, the acquisitions of these banks are more likely dependent on regulatory pressure to consolidate the banking sector rather than value maximization purposes. This regulatory pressure forces the acquisitions to be completed quickly. For example, the acquisition of Bank Jago, one of the largest digital banks in Indonesia, by GoTo, the most valuable startup in Indonesia, occurred only two months after the initial acquisition announcement. Similarly, the acquisition of SeaBank, another digital bank, by Shopee, a Singapore-based e-commerce company, happened one month following the acquisition announcement.

reduction. Our econometric strategy revolves around staggered DID estimators, both regular, interaction-weighted, and synthetic, to ensure the estimates are not contaminated by the biases that can arise due to staggered treatments and where the parallel trends assumption is weak. To further insulate our analysis from the possibility of an endogeneity bias, we complement our main findings with an instrumental variable (IV) estimator.

Why do we find a counter-intuitive relationship between digital transformation and liquidity creation? After their digital transformation, digital banks need to incur sizeable initial fixed costs related to infrastructure investments and the adoption of new technology to support their new business (Saka et al., 2022). If a bank size is insufficiently big, it tends to incorporate these additional costs more slowly and cannot achieve economies of scale (Feyen et al., 2021). Our results show that, because financial authorities prioritize the mergers and acquisitions of small-sized banks, the size of the newly established digital banks are relatively smaller than that of traditional banks, and they have less capability to exploit economies of scale. This increases business costs and lowers competitiveness, which ultimately leads to more expensive interest rates and impairs liquidity creation capability.

Our paper relates to two strands of literature. A large body of literature documents the determinants of bank liquidity creation. For example, Nguyen et al. (2020) examine the impact of Federal Reserve stress tests on US bank liquidity creation and find its negative effect on both on-and off-balance sheet bank liquidity creation. Prior studies also examine other determinants of bank liquidity creation, such as competition (Silva, 2019) and policy rate (Schelling and Towbin, 2022). A novel contribution of our paper is to empirically examine whether technological innovation is one of the determinants of bank liquidity creation and complement prior theoretical works.

Another growing strand of literature studies the effects of digital innovations in the financial industry. Evidence demonstrates how the spread of FinTechs can fill the credit gap (Allen et al., 2022; Buchak et al., 2018). Growing digital credit also positively contributes to entrepreneurship and financial inclusion, particularly in disadvantaged areas (Erel and Liebersohn, 2022; D'Andrea and Limodio, 2024). Unlike these articles that show the positive effects of digital innovations within FinTechs, our work speaks to the conditions where technological innovations in the banking sector become ineffective because of factors such as a bank's inability to achieve economies of scale and stringent regulation.

These findings shed new light on the dark side of the flourishing digital banks and FinTechs. Earlier research highlights how digital innovations can help financial institutions reduce funding cost, provide better products, and gain market share (Fuster et al., 2019). However, more recent research suggests that these benefits can only be possessed by a limited number of large financial institutions that can achieve economies of scale (Feyen et al., 2021). Many digital banks also have poor risk management, which increases their operating costs and undermines their financial intermediary functions (Koont et al., 2023). In addition to bank-level characteristics, industry-level characteristics also matter. A cross country study by Cornelli et al. (2023) shows that digital financial innovations are only effective as an alternative financial service if there is less stringent banking regulation, adequate market competition, more advanced judicial system, more developed capital markets, and greater ease of doing business, characteristics that are usually restricted to advanced economies. Therefore, our findings provide an alternative explanation where digitalization in banking fails to improve efficiency under certain bank-level and/or industry-level characteristics, and how this affects liquidity creation.

The paper is organized as follows. Section 2 summarizes prior research, provides the overview of Indonesian banking sector, and develops hypothesis. In Section 3 we show data sources, descriptive statistics, and outline the empirical model. We report our baseline results in Section 4. Section 5 discusses robustness checks, while Section 6 concludes.

2 Conceptual framework

2.1 Digitalization of the financial sector

Digitalization of the financial sector gave rise to the proliferation of new types of financial institutions such as digital banks and other FinTechs.[2] Literature suggests that this proliferation can be attributed to several factors. First, technological innovation in the financial industry prompts both start-ups and existing financial institutions to seek ways to automate, innovate, simplify, as well as speed up financial services. These innovations allow financial institutions to reduce operating costs that help them lend more cheaply, provide better products, and gain market share (Buchak et al., 2018; Thakor, 2020).

The second factor is related to product differentiation. Many digital financial institutions offer substantially different products from traditional banks that enable them to capture untapped market (Fuster et al., 2019). Thanks to their reliance on advanced algorithms and data-driven technology, these institutions are able to develop products aimed at specific borrowers (Allen et al., 2022; Bao and Huang, 2021; Bollaert et al., 2021) These factors help

[2] While FinTech is often defined as nonbank financial institutions that intensively depend on technology (Thakor, 2020), a digital bank (also known as neobank, online bank, or virtual bank) is a bank that offers its services only via the internet and other electronic means such as web applications, telephone, online chat, and mobile check deposit. In addition, different from FinTechs that often operate in regulatory sandboxes, digital banks are subject to standard banking sector's regulatory constraints (Buchak et al., 2018).

digital banks quickly develop and complement existing traditional banking system.

Another factor that drives the growth of digital banks and FinTechs can be associated with the efforts to improve financial inclusion, particularly where there is geographic constraint. Erel and Liebersohn (2022) investigate the impact of digital financial services on loan supply to small businesses underserved by traditional banks by exploiting the introduction of the Paycheck Protection Program in the US. Their results show that digital financial services are disproportionately used in areas with fewer bank branches, lower income, and limited banking relationships. D'Andrea and Limodio (2024) show that the availability high-speed internet helps banks adopt new financial technologies and expand credit supply to previously unreachable areas. In short, digitalization contributes to financial inclusion that ultimately increases liquidity in the economy.

2.2 Bank M&As in Indonesia

Indonesia has a bank-based financial system and its banking sector is characterized by monopolistic competition where the four largest banks control around 50% of the industry's total assets (Bank Indonesia, 2023). This market concentration undermines competition and reduces the efficiency of Indonesian banks. A handful of large banks control the majority of the industry by focusing on complex commercial and industrial (C&I) loans for corporations; while numerous small banks focus on niche markets more suitable for micro, retail and consumer loans, or become part of conglomerates that mostly finance within-group companies (Shaban et al., 2014).[3] Because of their limited capacity, small banks are unable

[3]Existing commercial banks in Indonesia are classified into four categories based on their core capital. Banks with core capital of at least Rp70 trillion are classified into Commercial Banks Group of Core Capital (KBMI) 4. Banks with core capital between Rp14-70 trillion, between Rp6-14 trillion, and less than Rp6

to grow and compete with large banks while simultaneously imposing additional risk to the financial system due to their substandard risk management procedure (Kovner and van Tassel, 2022).

This situation prompts the Indonesian Financial Services Authority (OJK) to consolidate the banking sector and reduce the number of smaller banks because they are inefficient and undervalued (Shaban and James, 2018). To do this, the OJK puts barriers to entry by requiring minimum paid-in capital of Rp3 trillion ($\approx$ \$200 million) to establish a new bank, while the majority of existing banks still have paid-in capital significantly below that figure.[4] Since the cost of establishing a new bank is too high, no new banks were ever established since the 1997 Asian Financial Crisis. Instead, the OJK encourages the consolidation of smaller banks through M&As so these banks can receive sufficient capital, managerial skill, as well as business know-how to benefit from economies of scale.

Because M&As are driven by regulatory pressure rather than bank performance, they are usually completed relatively quickly and not intended for shareholder value maximization (Berger et al., 1999; Pilloff, 2004; Shaban et al., 2014). As shown by Online Appendix Table A.1, the median value of merger and acquisition process in Indonesia is 2 months, with an average of 4.6 months. Smaller banks are preferred to be acquired to speed up integration process, while their performance becomes less relevant.[5]

Since the regulation became effective, the number of commercial banks in Indonesia has

trillion are categorized as KBMI 3, KBMI 2, and KBMI 1 banks, respectively. There are four KBMI 4 banks that control around 50% of the industry's total assets. Banks within KBMI 1 and KBMI 2 categories are more numerous but only control less than 30% of the industry's total assets. Figure D.1a illustrates the distribution of Indonesian banks according to their KBMI category.

[4]This minimum requirement was later increased to Rp10 trillion (\$500 million) in 2021.

[5]More sizeable M&As, even though less common, usually involve large foreign banks such as when HSBC Group, a British multinational universal bank, was integrated with Bank Ekonomi, a local bank, in 2017.

been declining. Total operating commercial banks in Indonesia have declined from 120 banks in 2010 to 107 banks in 2021. The appearance of digital banks since the late 2010s has contributed further to this reduced number of banks. The OJK urges banks to hasten industry consolidation process and digitalize banks through M&As to improve industry efficiency and financial inclusion (OJK, 2020). Similar to previous trend, however, the selection of target banks depends more on regulatory direction rather than the performance of the target banks.

2.3 Hypothesis development

Bank intermediary function can be captured by their ability to create liquidity in the economy. Specifically, this is carried out by drawing short-term or liquid liabilities and transforming it into long-term or illiquid assets (Diamond and Dybvig, 1983). An extensive literature has shown various determinants of bank liquidity creation such as corporate actions, financial regulation, and industry characteristics (Nguyen et al., 2020; Silva, 2019). In this paper, we focus on the effect of technology on bank liquidity creation, which is a relatively less explored topic in the literature.

Theoretical models that examine the role of innovation and technology in the banking sector date back to the works of Diamond (1984) as well as Boot and Thakor (2000). These models suggest that banks enhance technological innovation and efficiency to reduce transaction costs, improve monitoring, maintain competitiveness, and generate market integration. Empirically, prior research shows that effective implementation of technological innovation within digital banks and other FinTechs can improve internal governance and control, and reduce unnecessary delays in the decision-making process (Buchak et al., 2018; Fuster et al., 2019). In terms of service offerings, digital innovations enable financial institutions to capture untapped market by improving loan access for the marginal firms and contributing to financial inclusion with less variable costs relative to brick-and-mortar outlets (Allen et al., 2022; Bao and Huang, 2021; Bollaert et al., 2021; Buchak et al., 2018; Erel and Liebersohn, 2022; Fuster et al., 2019). Meanwhile, lower cost pressures enable banks to better perform their liquidity creation function (Schelling and Towbin, 2022). Based on this premise, we conjecture that digital transformation in banking improves operational efficiency that ultimately increases liquidity creation.

Concurrently, even though technological innovation may lead to better operating efficiency and higher market share, digital banks need to incur high initial fixed costs associated with digital infrastructure investment (Saka et al., 2022). These sunken costs may include the costs of adopting, learning, and optimizing the necessary technology when switching from a traditional bank to a full-fledged digital bank. Large banks can speed-up the transition process and minimize these costs by amortizing these costs over a large customer base (Feyen et al., 2021). However, if a bank is too small and too slow to incorporate this new technology into its new business model, it may fail to achieve economies of scale and the transition period may continue for a large amount of time. Sustained high operational costs can reduce efficiency and increase cost of fund because banks need to maintain their profit margin, leading to higher loan rates and reduced competitiveness. These higher loan rates tighten credit supply and eventually reduce the bank liquidity creation (Kovner and van Tassel, 2022).

In addition, industry-specific factors may also affect digital banks' liquidity creation. Prior research shows how factors such as macroeconomic environment and institutional framework can affect a country's financial sector development (Acemoglu et al., 2009). As described in Section 2.2, Indonesian banking sector is characterized by stringent regulations and limited competition, where most bank M&As are regulatory driven that pay less attention to shareholder value creation purpose. These factors may significantly undermine the country's digital transformation process and adversely affect non-traditional credit development provided by digital banks and other FinTechs (Cornelli et al., 2023).

3 Empirical design

3.1 Outcome variables

The key dependent variables in the empirical analysis measure bank liquidity creation, various balance sheet items, and interest rates. We discuss the construction of each in turn.

3.1.1 Berger and Bouwman's (2009) bank liquidity creation

To measure liquidity creation, we use the Berger and Bouwman (2009) liquidity creation measure. This measure is useful for our study because it can be decomposed into on- and off-balance sheet components, which allows us to examine which aspects of balance sheet influence bank liquidity creation the most after digital transformation.

Berger and Bouwman (2009) provides four versions to measure liquidity creation. In this paper, we use the recommended 'cat fat' variant that classifies the liquidity of loan items based on loan category ('cat') rather than maturity, and incorporates off-balance sheet items into the liquidity creation measure ('fat').[6] Prior research prefers this variant because loan

[6]Other variants are: 1) 'mat fat', which uses loan items based on maturity ('mat') and incorporate off-balance sheet items; 2) 'cat nonfat', which uses loan items based on loan category but does not incorporate off-

category is more important in determining the ability of banks to securitize and sell loans rather than loan maturity, thus more important in defining liquidity creation (Nguyen et al., 2020). Online Appendix Table A.2 provides details of the construction of liquidity creation measures.

3.1.2 Balance sheet items and interest rates

We also use various bank balance-sheet and income statement items as the dependent variables to complement our baseline analysis. Specifically, we use loans to assets, deposits to assets, operating expenses to operating income, as well as return on assets and return on equity. Finally, we employ interest rates data, both lending rate and saving rate, to examine cost of fund components. Because we cannot directly retrieve interest rates data, we compute interest rate variables by dividing each interest income (expenses) item with its respective interest-bearing assets (liabilities).

3.2 Data and descriptive statistics

We construct a quarterly panel of Indonesian banks from 2014Q1 to 2022Q3. We retrieve quarterly bank-level financial data from the OJK's Commercial Bank Report. For each bank, this provides quarterly information on total assets, loans, deposits, equity, as well as other balance sheet, off-balance sheet and income statement items. We use these variables to construct Berger and Bouwman (2009) liquidity creation measure. We exclude sharia banks that are subject to a different regulatory framework. This provides an unbalanced sample of

balance sheet items; and 3) 'mat nonfat' that uses loan items based on maturity and does not incorporate off-balance sheet items.

3,621 observations for 108 banks, including 9 digital banks in the treatment group (or about 8.3% of total observations). Table 1 provides the description of each variable in the data set.

[Insert Table 1] [Insert Table 2]

Table 2 reports summary statistics for the dependent variables as well as the control variables of interest. The average liquidity creation, LCI, is 16.3%. When we deconstruct liquidity creation measure into asset-side ($LCIA$), liability-side ($LCIL$), and off-balance sheet ($LCIO$), the averages are 15.8%, -8.6%, and 9.0%, respectively. Consistent with Berger and Bouwman (2009), while asset-side liquidity creation is the main driver of bank liquidity creation, a considerable proportion the liquidity is created off-balance sheet. This finding justifies the use of the 'cat fat' version of liquidity creation measure.

Moving on to balance sheet items, the average loans and deposits comprise 47.7% and 54.0% of total assets, respectively. C&I loans are the largest contributor to bank lending, while time deposits are the largest contributor to bank deposits. The mean lending rate is 12.5% and that of the deposit rate is 5.1%. Finally, the mean value of net interest margin in our sample is 4.5%.

3.3 Econometric specification

We estimate a staggered DID model with two-way fixed effects (TWFE) to quantify the effects of digital acquisition. Because the conversion from traditional banks into digital banks occur at different periods, the shocks are staggered over the sample period and affect the dependent variable at different quarters. Banks that do not convert into digital banks throughout the sample period are categorized into the control group. Banks that transform into digital banks are in the treatment group. Specifically we estimate:

$$y_{i,t} = \beta \cdot Digital_{i,t} + \gamma \cdot X_{i,t} + \phi_i + \phi_t + \epsilon_{i,t}, \tag{1}$$

where $y_{i,t}$ is the outcome variable of interest for bank i in quarter t; $Digital_{i,t}$ is equal to one if a bank is acquired and converted into a digital bank and zero otherwise; $X_{i,t}$ is a vector of bank covariates or control variables; ϕ_i and ϕ_t are bank and quarter-year fixed effects, respectively; $\epsilon_{i,t}$ is the error term. Following existing banking as well as merger and acquisition literature (Chen and Vashishtha, 2017; Lin, 2022; Nguyen and Phan, 2017), our control variables include log assets ($Size$), loan loss provisions to assets (LLP), off-balance sheet commitments to assets (OBS), subordinated debt to assets ($Subdebt$), and z-score or distance to default ($Zscore$). The standard errors are clustered at the bank level.

DID estimations require two assumptions. First, assignment to treatment is plausibly exogenous with respect to bank liquidity creation, suggesting liquidity creation is not driving digital acquisitions. Second, in the absence of treatment, changes in bank liquidity creation are similar for treatment and control groups. This is the parallel trends assumption.

We first examine the exogeneity of digital acquisitions. Literature suggests that M&As in the banking sector can be driven by value and non-value maximizing motives (Berger et al., 1999).[7] The latter usually occurs when there are strong regulatory and structural forces that are exogenous to bank performance including liquidity creation capability (Chen and Vashishtha, 2017; Pilloff, 2004). This postulation reflects M&A transactions in Indonesia,

[7]Even when an M&A motive is value maximization, it can still be hard to predict. Literature documents the unpredictability of acquisitions because they are considered major yet discretionary decisions (Nguyen and Phan, 2017; Phan, 2014) that do not necessarily depend on the fundamentals of the target companies (Chen and Vashishtha, 2017; Lin, 2022).

where financial authorities have an active goal to restructure the banking industry (Shaban and James, 2018). Due to this regulatory force, M&A transactions in Indonesia tend to be unpredictable, complete quickly, and not depend on the performance of the target banks. Figure 1 depicts the kernel density estimates for the target banks (treatment group) and other banks (control group) in 2018, one year prior to the first occurrence of digital bank acquisition. The estimates highlight the comparable characteristics of the treatment and control groups prior to the acquisition, and reflect that target banks are not necessarily underperforming.

[Insert Figure 1]

We examine further the exogeneity of digital acquisitions by following the test outlined by Calderon and Schaeck (2016) and estimate the conditional probability of a digital acquisition using Cox (1972) proportional hazard models. Our key explanatory variable captures bank liquidity creation and other control variables discussed earlier. We focus on the time from the start of our sample to the occurrence of digital acquisition. The hazard rate $h(t)$ represents the likelihood that a digital acquisition is observed at time t in bank i, given that there was no digital acquisition until t. We use a Cox model that does not impose a shape on the hazard function:

$$h\left(\frac{t}{x_i}\right) = h_0(t)\exp(x_i\beta_x), \tag{2}$$

where $h_0(t)$ denotes the baseline hazard, and β_x is the vector of parameters. A significant coefficient for the liquidity creation increases the hazard of digital acquisitions. Panel A of

Table 3 shows that the effect is insignificant and confirms that digital acquisitions in Indonesia do not depend on bank liquidity creation, that is, the exogeneity of digital acquisitions.

[Insert Table 3]

Additionally, we perform balancedness test outlined by Pei et al. (2019) to ensure that digital transformation is not systematically correlated with the control variables. First, we regress digital transformation dummy on the control variables:

$$Digital_{i,t} = \alpha + \beta \cdot X_{i,t} + \phi_i + \phi_t + \epsilon_{i,t}, \tag{3}$$

where $Digital_{i,t}$ is a dummy variable denoting bank i's digital transformation at time t; and $X_{i,t}$ is a vector of explanatory variables. We cluster the standard errors at the bank level. The results in column 1 of Panel B, Table 3 show that our control variables do not significantly influence bank acquisition decisions. Then, we aim to detect potential confounds by placing digital transformation dummy on the right-hand side of the equation (Pei et al., 2019). We then regress individual control variables on digital transformation dummy and bank size. The results in columns 2-5 of Panel B demonstrate that none of the balancing regressions yields a systematic correlation between digital transformation dummy and any of the control variables. These findings suggest that our findings are not likely explained by selection on observables.

[Insert Figure 2]

Next, we examine parallel trends assumption that requires similar changes in bank liquidity creation between digital banks and other traditional banks. As suggested by Calderon and Schaeck (2016), the assumption does not require identical levels of liquidity creation between treatment and control group. We therefore estimate the annual changes of bank liquidity creation and estimate:

$$\Delta y_{i,t} = \beta_t \cdot (T_i \times \phi_t) + \phi_i + \phi_t + \epsilon_{i,t}, \tag{4}$$

where $y_{i,t}$ is the annual change of bank liquidity creation and T_i is a dummy variable representing treatment banks. Figure 2 illustrates the evolution of bank liquidity creation between digital and traditional banks during the sample period by plotting the estimates of β_t. Prior to the first digital bank acquisition, liquidity creation of digital and traditional banks evolves similarly within the two groups. Almost all the pre-digital bank acquisition coefficient estimates of β_t are statistically insignificant, suggesting the parallel trends identifying assumption holds.

4 Main findings

Table 4 reports estimates of Equation (1). Column 1 shows the effect of digital transformation on the asset side of the balance sheet. The coefficient of interest shows asset-side liquidity creation falls by 14.5 percentage points and this is significant at 1%. This implies that digital banks have significantly lower liquidity creation capability relative to its traditional bank counterpart. Estimates in columns 2 and 3 show insignificant effects of digital transformation on liability-side and off-balance sheet liquidity creation. The net effect of these changes is lower overall liquidity creation. Column 4 indicates that digital banks have a significantly 14.1 percentage points lower liquidity creation.

Next, we examine whether digital banks' lower liquidity creation capacity is associated with their lower market share. To do this, we estimate Equation (1) using each bank's market share as the outcome variable. Column 5 of Table 4 suggests that banks lose their market share by an average of 0.2 percentage point after being converted into digital banks. Considering Indonesian banking sector total assets of $666.7 million (Rp10 trillion) as of 2022Q3, this market share reduction is equivalent to $1.3 million (Rp20 billion) per bank.

[Insert Table 4]

Among the control variables, the results show that larger banks tend to have significantly higher asset-side liquidity creation, attributed to their economies of scale. However, bank size is negatively correlated with off-balance sheet liquidity creation. There is a positive effect of off-balance sheet commitments on all aspects of bank liquidity creation. We find no significant association between bank liquidity creation and loan loss provision as well as subordinated debt. The z-score is significantly negatively correlated with liability-side and total liquidity creation variables.

The key message emanating from Table 4 is that digital transformation does not guarantee a bank's ability to expand its liquidity creation. Prior studies show that FinTechs, including digital banks, can thrive only if they can exploit economies of scale and use their technological innovation to improve efficiency, speed up financial services, as well as offer innovative products (Feyen et al., 2021; Fuster et al., 2019; Saka et al., 2022). In other words, technological adoption alone is insufficient to increase liquidity creation if a bank has limited capacity to exploit economies of scale and achieve efficiency.

We therefore examine the relationship between a bank's liquidity creation and its ability to achieve economies of scale, represented by log assets ($Size$). To establish whether there exist heterogeneous relations between size and bank capability to create liquidity, we perform non-parametric estimation using polynomial splines of order 2.[8] We visualize the results by estimating the predictive margins with 95% confidence intervals for digital banks and other banks. Figure 3a graphically presents the econometric results of this test.

[Insert Figure 3]

We can draw two inferences from Figure 3a. First, it shows heterogeneous effects across the bank size distribution. The effect sizes tend to be greater for larger banks. This finding is intuitive because larger banks have more capacity and the economies of scale to create liquidity in the economy. Second, across the bank size distribution, the marginal effect sizes are larger within traditional banks. Digital bank needs a minimum log assets greater than 30.1 or $786.7 million (Rp11.8 trillion) to generate positive liquidity creation, while the minimum threshold for traditional banks is much smaller than that. This finding may be explained by the initial fixed costs required to establish a digital bank. If a digital bank is too small, it is less able to exploit economies of scale and has to incur high initial fixed costs. Because fixed costs depend less on bank size, banks need to be sufficiently large to be able to fully benefit from digital transformation. Figure 3b illustrates the histogram of log assets within digital banks and confirms that the majority of digital banks do not have assets above the minimum threshold (or the capacity to achieve economies of scale) to positively create liquidity.

[8] Our non-parametric regression has two covariates bank size ($\mathbf{x}_{i,t}$) and digital bank dummy ($\mathbf{z}_{i,t}$), as estimate: $y_{i,t} = g(\mathbf{x}_{i,t}\mathbf{z}_{i,t}) + \epsilon_{i,t}$, where $E(y_{i,t}|\mathbf{x}_{i,t}\mathbf{z}_{i,t}) = g(\mathbf{x}_{i,t}\mathbf{z}_{i,t})$. A 2nd-order polynomial of $x_{i,t}$ and $z_{i,t}$ therefore would have terms $(x_{i,t}, z_{i,t}, x_{i,t}z_{i,t}, x^2_{i,t}, z^2_{i,t}, x^2_{i,t}z^2_{i,t})$.

Next, we examine the effects of digital bank on individual balance sheet components to examine which aspects of balance sheet drive the reduction of liquidity creation within digital banks. In columns 1-3 of Table 5, we estimate Equation (1) using C&I loans, consumer loans, and total loans, respectively, as the outcome variables. In column 1 of the table we find digital transformation significantly decreases the share of C&I loans to assets by 11.7 percentage points. Based on liquidity creation methodology outlined by Berger and Bouwman (2009), C&I loans are considered as illiquid assets that create liquidity in the economy, and one of the largest contributors to asset-side liquidity creation. This explains why the estimated coefficient β in the asset-liquidity creation regression (Column 1 of Table 4) is similar to that C&I regression (Column 1 of Table 5). Column 2 of Table 5 reports estimates of Equation (1) using consumer loans to assets as the dependent variable. Our variable of interest, however, is statistically insignificant. Finally, column 3 of the table presents the effect of digital transformation on total loans to assets. The estimated coefficient is negative and significant at the 1% level. Economically, the estimates show digital banks' total loans to assets declined by 9.4 percentage points relative to the control banks.

[Insert Table 5]

Now we turn our discussion to bank deposits. Columns 4-7 of Table 5 present estimates of Equation (1) using saving deposits, demand deposits, time deposits, and total deposits, respectively, as the dependent variables. In columns 4 and 5 of Table 5, the coefficients of interest are statistically insignificant. Both saving deposits and demand deposits appear invariant to digital transformation. Column 6 of Table 5, however, shows negative and significant correlation between digital bank and time deposits to assets. Despite this significance, Berger and Bouwman (2009) consider time deposits as semiliquid liabilities that do not contribute to banks' liability-liquidity creation. This further confirms the insignificant β in column 2 of Table 4. In column 7 of Table 5 we find that digital transformation significantly decreases total deposits to assets by 12.2 percentage points.[9]

4.1 Digital bank and cost of funds

Our main results show that digital transformation reduces a bank's ability to create liquidity if its size is lower than a certain threshold. Now we discuss why economies of scale and the capability to amortize costs over a large customer base are important for digital banks by examining the effect of digital transformation on a bank's operating efficiency and cost of funds. Similar to prior research (González, 2009; Safiullah and Shamsuddin, 2019), we measure operating efficiency using the ratio of operating expenses to operating income. We then estimate Equation (1) by dividing the sample into small and non-small banks based on the threshold we obtain from Figure 3 (i.e., log assets=30).

[Insert Table 6]

Table 6 presents the sub-sample estimates. Column 1 shows the regression result for small banks, while column 2 reports that for non-small banks. The coefficient of interest is positive and statistically significant in both columns, even though the magnitude is almost twice as large for small banks. Consistent with prior research (Feyen et al., 2021; Saka et al., 2022), our findings show that digital transformation increases operating costs and the costs

[9] Online Appendix Table C.1 shows the decrease in loans to assets (deposits to assets) is offset by the increase in securities to assets (equity to assets). Securities to assets and equity to assets are considered as liquid assets and illiquid liabilities that decrease bank liquidity creation.

are larger when banks have smaller size, indicating their inability to amortize these costs. In column 3, we use all sample and interact digital transformation with a dummy variable equal to one if a bank is small and zero otherwise. The results validate our previous findings in which digital transformation in smaller banks lead to higher operating costs and overheads after the transformation.

Higher overheads undermine a bank's competitiveness as well as its ability to manage interest rates and create liquidity in the economy (Calderon and Schaeck, 2016; Claessens et al., 2018; Kovner and van Tassel, 2022). Hence, we test how interest rates respond to digital transformation. Specifically, we estimate Equation (1) using lending and saving rates as the outcome variables.

[Insert Table 7]

Columns 1-3 of Table 7 present the effects of digital transformation on lending rates. In column 1 we find digital transformation leads to a significant 2.9 percentage points increase in C&I loans rates. The findings in column 2 corroborate this result. Specifically, digital banks have a significant 3.9 percentage points higher consumer loans rates. Column 3 of Table 7 highlights the effect on the overall lending rates. The variable of interest is positive and significant at the 5% level. Economically, the estimates show lending rates increased by 3.9 percentage points after the conversion into digital banks.

In columns 4-7 of Table 7 we study the effect of digital acquisition on deposits rates. The estimates in columns 4 and 6 show that both demand deposit and time deposit rates did not significantly react to digital transformation. However, we find positive and significant effect of digital bank on saving deposit rates (column 5) even though the magnitude is economically insignificant. Column 7 of Table 7 shows the effect on overall deposit rate, which is statistically insignificant.

Now we investigate how the evolution of digital banks' interest rates affects its interest rate spread using net interest margin. Column 8 of Table 7 indicates that net interest margin within digital banks increased by 1.2 percentage points after their establishment. The coefficient is significant at the 5% level. High net interest margin may reflect two possible explanations. First, high net interest margin reflects strong bank pricing power derived from robust market position and limited competition (Claessens et al., 2018). Our results in Table 4 have shown that this does not apply to digital banks in Indonesia because of their relatively smaller size and stagnating market share. Alternatively, high interest spread can be attributed to internal factors such as high operating expenses and cost of funds as well as low competitiveness (Calderon and Schaeck, 2016). The latter is more likely to explain our findings.

4.2 Potential heterogeneity of digital acquisition

The consistency of our staggered DID estimation relies on the standard "common trends" assumption. However, recent econometric literature suggests that this assumption is often implausible (Baker et al., 2022; Sun and Abraham, 2021). In our setting, it is possible that digital transformation has a heterogeneous effect. For example, the effect of digital acquisition during the COVID-19 lockdowns (2020Q2-2021Q3) on liquidity creation may differ from that in other periods.

We follow Sun and Abraham (2021) who propose an interaction-weighted (IW) DID estimator to establish the robustness of the baseline results. The estimator focuses on the weighted average of 'cohort-specific average treatment effects on the treated' ($CATT$) for a particular event group e and their relative time periods l, and is robust to heterogeneous treatment effects across cohorts. Online Appendix B.1 describes the IW-DID estimator methodology.

[Insert Figure 4]

Figure 4 plots the dynamic coefficient estimates of this test for all bank liquidity creation variables and illustrates that in most quarters prior to digital acquisition the dynamic coefficient estimates are insignificant. Banks therefore do not anticipate digital acquisition nor preemptively change their behavior, consistent with parallel trends. However, at $t \geq 0$, that is, the quarter starting from the occurrence of a digital acquisition, most coefficient estimates show that asset-side liquidity creation and total liquidity creation significantly decrease.

This test produces two important insights. First, we find consistent results irrespective of whether we use a two-way fixed effects or IW-DID estimator. The baseline findings are thus not attributable to methodological problems that arise due to the staggered digital acquisitions. Second, the IW-DID estimator reveals that the decrease in bank liquidity creation of digital banks remains significant until eight quarters or two years after the acquisition, which indicates that the effect of digital acquisitions on bank liquidity creation does not dissipate over time.

4.3 Addressing weak parallel trends

One of the biggest challenges of a DID setting is satisfying the parallel trends assumption. The counterfactual in our tests are traditional banks that are relatively larger than digital banks. Even though our baseline equation attempts to remove time-invariant size using the bank fixed effects, traditional banks may differ from digital banks in other ways over time that make it difficult to compute the implied counterfactual. One solution to this challenge is the application of synthetic control (SC) method that construct a matched synthetic control from a larger number of potential donor units (Abadie et al., 2010; Cavallo et al., 2013).

However, a common pitfall in SCM is the requirement that the treatment group needs to be trending on similar levels prior to a shock.[10] Arkhangelsky et al. (2021) propose the synthetic DID (SDID) that brings in strengths from both the DID and SC methods – namely by loosening the parallel trend assumptions, for DID, and dismissing the necessity that the treatment group be housed within a "convex hull" of the control group, for SCM.

Because SDID requires a balanced panel, we drop banks that do not have complete observations over the sample period, resulting in a sample of 3,255 observations for 93 banks. Similar to SCM, SDID estimates weights that align pre-exposure trends in the outcome of unexposed units with those for the exposed units. Then it uses these weights in a basic staggered fixed effects regression to estimate the average treatment effect (ATE), which localize the SDID estimator. Online Appendix B.2 describes the SDID estimator methodology.

[Insert Table 8]

To pin down econometric estimates of the magnitudes, we calculate the post digital

[10] This is different from standard DID estimators, which allow for treatment and control groups to be trending on entirely different levels.

transformation average quarterly effect for each outcome variable and the corresponding p-value. Estimates in Table 8 are consistent with our baseline staggered DID and IW-DID results. Despite using an alternative methodology, the inference of the treatment effects are considerably similar to those obtained using staggered DID analysis.

4.4 Instrumental variable regressions

Digital acquisitions may be endogenous to banks' current performance and are therefore may not be randomly assigned. We address this issue with an instrumental variable estimator using accumulated capital injections from six to ten quarters prior to the digital acquisition event. This instrument is plausibly exogenous because contemporary balance sheet compositions are unrelated to historic capital injections (Raz et al., 2022). Historic capital injections also cannot endogenously react to contemporary digital acquisitions. The instrument is, however, relevant because capital level is correlated through time, i.e., past capital level affects current capital adequacy (Berger and Bouwman, 2013; Kang and Park, 2021).

[Insert Table 9]

Table 9 confirms our previous results. Our coefficient of digital acquisition is negative throughout all cells of these columns. In column 4 of Table 9, which is of our main interest, the estimate is even more potent economically compared to that of the equivalent column of Table 4. Meanwhile, the first-stage results show that the coefficient of accumulated capital injection is always statistically significant at the 1% level. Our first-stage F-tests also reject weak instruments, implying that we obtain statistics above the tabulated critical values for a size bias of 10% relative to ordinary least squares (OLS). Our instrumental variable estimation strategy therefore alleviates potential concerns regarding endogeneity and simultaneity bias.

4.5 Randomization Inference

Another concern of our empirical specification is related to the validity of the standard errors in DID settings when the number of treated observations is small relative to total sample size. In our case, the treatment group only comprises 8.3% of the sample. To address this issue, we perform a randomization exercise as outlined by Conley and Taber (2011). Specifically, we randomly assign false treatment to the control banks and we estimate Equation (1) repeatedly for 1,000 times using each outcome variable, namely LCI, $LCIA$, $LCIL$, and $LCIO$.

Online Appendix Figure C.1 document the distribution of the simulation results. We can infer two conclusions. First, the false treatment effects have a mean value of zero. Second, for LCI, $LCIA$, and $LCIL$, the real treatment effects (the effects of digital transformation obtained from Table 4) indicated by the solid line lies to the left-hand side of the bottom fifth percentile of the distribution indicated by the dotted line. This evidence confirms the validity of our baseline findings and allaviates concerns regarding the validity of the inferences computed using low number of treatment observations.

5 Robustness checks

We conduct sensitivity tests and further robustness checks to ensure that our main findings are not driven by unobservable confounds. Prior research documents the unpredictable nature of acquisitions, thus making anticipation unlikely. Our parallel trend and IW-DID estimates have shown that this is not the case. Nevertheless, we examine this issue further to ensure the exogeneity of our shock. We amend our baseline model with an anticipation dummy, *Anticipation*, that is equal to one during the two quarters preceding the transformation into a digital bank and zero otherwise. Estimates in column 1 of Online Appendix Table C.2 show that the result confirms our previous findings. Next, even though digital banks in Indonesia were established via acquisitions, other acquisitions not intended to establish digital banks also occurred concurrently in our sample period. We therefore extend Equation (1) by including these other acquisitions. Specifically, we include an acquisition dummy, *Acquisition*, that is equal to one during and after the occurrence of non-digital acquisition. In column 2 of Online Appendix Table C.2 we find that the results are robust to this change. Finally, the outbreak of COVID-19 pandemic that forced most countries to restrict mobility through the implementation of a series of lockdowns had provided the public with alternative technology-based financial services, which are less reliant on traditional brick-and-mortar office branches (Saka et al., 2022). To control for this factor, we interact our variable interest with COVID-19 dummy that is equal to one from 2020Q2 onward. Column 3 of Online Appendix Table C.2 shows that our baseline findings remain consistent.

A potential unintended consequence of digital transformation is its spillover effects on other traditional banks.[11] To investigate whether such effect is present, we examine the impact of digital transformation on the market share of traditional banks. Online Appendix Table C.3 show no such effect present. This evidence implies that the negative effect of

[11]The Boot and Thakor (2000) model predicts that banks invest more to increase the value of their relationship loans when they face higher competition. This suggests that traditional banks become more enterprising to maintain their business in response to additional competition posed by digital banks.

digital transformation on liquidity creation is not due to retaliatory measures by traditional banks (spillover effects).

Larger banks may behave differently from smaller banks. Evidence shows that small banks are more likely to be the target of an acquisition (Berger et al., 1999; Pilloff, 2004). We therefore re-estimate Equation (1) by restricting our sample size to banks with total asset equal to or smaller than that of digital banks. Panel A of Online Appendix Table C.4 demonstrates the results are robust. We conduct a similar test by restricting our sample size to KBMI 1 and KBMI 2 category banks, that are often the target bank acquisitions. The findings in Panel B of Online Appendix Table C.4 remain consistent. Because the four largest (KBMI 4) banks are significantly larger, they may behave differently from other banks. We therefore re-estimate our baseline model by excluding these banks. The results in Panel C of Online Appendix Table C.4 remain robust.

Bank intermediary function may be affected by the levels of industry competition (Claessens et al., 2018; Liebersohn, 2024). To ensure that our results are not driven by this factor, we follow prior research by interacting our coefficient of interest with net interest margin, which is a proxy for bank competitiveness (Calderon and Schaeck, 2016). Panel A of Online Appendix Table C.5 documents that the results are robust to this change. Our findings may be confounded by the selection of 'bad controls'. We therefore re-estimate our baseline model without control variables. The results in Panel B of Online Appendix Table C.5 remain consistent.

Omitted variable bias may not be captured by sensitivity analysis alone because the magnitude of the bias depends on coefficient movements that are scaled by the change in R-squared. We complement our sensitivity analysis by conducting coefficient stability test outlined by Oster (2019). The test constructs parameter bounds that assess robustness to omitted variable bias based on R-squared movements and assumes that selection on unobservables is proportional to selection on observables. Online Appendix Table C.6 highlights that the bounds for our main outcome variables exclude zero and confirm the robustness of our baseline findings.

6 Conclusions

Examining the relationship between digital technology and bank liquidity creation is empirically challenging due to their endogeneous relationship and the difficulty in establishing counterfactuals. In this paper, we study the effect of digital transformation on bank liquidity creation by exploiting Indonesia's unique regulatory environment in which the financial authority actively prompts banks to conduct M&As. Prior research shows that M&As are arguably exogenous if they are enforced by financial authorities and not driven by value maximization purpose.

Using a staggered DID estimation strategy, our empirical findings show that digital transformation decreases liquidity creation by 14.1 percentage points, mostly due to the reduction of asset-side liquidity creation. Lower liquidity creation also decreases the market share of digital banks relative to that of traditional banks. Digital banks' lower liquidity creation is driven by their inability to benefit from economies of scale, leading to high cost of fund following the slow normalization of the high initial fixed cost necessary to adopt the new technology and lower competitiveness.

Our findings provide novel insights into the unintended consequences of digital transformation in the banking sector. Existing literature shows the positive benefits of digital transformation such as lower funding cost, the ability to provide better products, and enhanced loan screening capability. This evidence, however, comes with a caveat. To be able to reap these benefits, banks need to be sufficiently large because they have to absorb high initial fixed costs associated with digital infrastructure investment and achieve economies of scale. Failing to do so will increase a bank's operating costs that ultimately undermine its financial intermediary functions.

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Tables

Table 1: Variable descriptions

Variables	Definition	Unit
Dependent variable		
$LCIA$	Asset-side liquidity creation	Per cent
$LCIL$	Liability-side liquidity creation	Per cent
$LCIO$	Off-balance sheet liquidity creation	Per cent
LCI	Total liquidity creation using “cat fat” version of liquidity creation outlined by Berger and Bouwman (2009)	Per cent
$Share$	Market share in terms of total assets	Per cent
$C\&I\ loans$	C&I loans to assets	Per cent
$Consumer\ loans$	Consumer loans to assets	Per cent
$Total\ loans$	Total loans to assets	Per cent
$Saving\ deposits$	Saving deposits to assets	Per cent
$Demand\ deposits$	Demand deposits to assets	Per cent
$Time\ deposits$	Time deposits to assets	Per cent
$Total\ deposits$	Total deposits to assets	Per cent
$C\&I\ loan\ rate$	C&I loan rate	Per cent
$Consumer\ loan\ rate$	Consumer loan rate	Per cent
$Total\ loan\ rate$	Lending rate	Per cent
$Saving\ deposit\ rate$	Saving deposit rate	Per cent
$Demand\ deposit\ rate$	Demand deposit rate	Per cent
$Time\ deposit\ rate$	Time deposit rate	Per cent
$Total\ deposit\ rate$	Deposit rate	Per cent
NIM	Net-interest margin	Per cent
$Overheads$	Operating efficiency measure, which is the ratio of operating expenses to operating income	Per cent
Control variable		
$Size$	Log assets	Logarithm
OBS	OBS commitments to assets	Per cent
LLP	Loan loss provisions to assets	Per cent
$Subdebt$	Subordinated debt to assets	Per cent
$Zscore$	Distance to default. $Zscore = \frac{ROA+CAR}{\sigma ROA}$, where ROA is return on assets, CAR is the capital ratio, and σ denotes the standard deviation.	Standard-deviation unit
Instrument variable		
$Injection$	Accumulated capital injection between six quarters and ten quarters prior to digital acquisition	Per cent

Notes: This table provides a definition of each variable used in the empirical analysis. For brevity we suppress the variables' subscripts in the manuscript.

Table 2: Summary statistics

Variables	Mean	Median	sd	p10	p90
LCIA	15.8460	17.3492	13.8426	-2.3540	32.1058
LCIL	-8.5740	-7.5332	11.6951	-22.8811	6.2329
LCIO	8.9962	5.4388	10.4143	1.1965	24.0981
LCI	16.2682	15.8413	16.4080	-0.9238	34.1740
Share	0.9573	0.1744	2.7956	0.0324	1.6389
C&I loans	32.9776	33.1001	18.0250	8.4364	57.5089
Consumer loans	14.7110	9.4147	15.1963	0.1094	40.6248
Total loans	47.6887	49.1446	13.4763	29.5910	63.7125
Saving deposits	9.7537	8.0869	7.9101	1.3938	21.7081
Demand deposits	13.0792	10.3341	10.3501	2.6203	28.4345
Time deposits	31.2046	29.2801	15.9876	10.4613	54.9581
Total deposits	54.0376	56.3411	15.2674	32.5503	70.9630
C&I loan rate	11.8706	11.4282	4.6609	8.5461	14.3257
Consumer loan rate	13.4657	12.4239	6.8748	7.8075	18.9967
Total loan rate	12.4817	11.7294	5.9233	8.4782	15.3888
Saving deposit rate	2.4321	2.2188	1.4699	0.9871	4.1546
Demand deposit rate	2.4273	2.3491	1.1873	1.0744	3.8325
Time deposit rate	6.6664	6.8960	2.4924	3.6581	9.0274
Total deposit rate	5.1033	4.9404	2.1328	2.5907	7.7694
NIM	4.5140	4.4100	2.5803	1.7100	7.2900
Overheads	86.9939	85.0400	25.7020	67.3100	99.3000
Size	30.8775	30.7179	1.6359	28.9894	32.9735
OBS	3.0188	0.5883	5.2383	0.0000	10.0120
LLP	1.3216	0.8445	2.9537	0.2086	2.4518
Subdebt	0.4076	0.0000	1.0019	0.0000	1.6465
Zscore	19.9137	10.3800	33.6363	2.2059	44.8190
Inject	0.7982	0.0000	3.6258	0.0000	1.5433

Notes: This table provides the summary statistics for the variables used in the empirical analysis. Variable definitions are provided in Table 1.

Table 3: Exogeneity of digital transformation

Panel A: Cox (1972) proportional hazard (Cox PH) model

Dependent variable	(1) *Digital*	(2) *Digital*	(3) *Digital*	(4) *Digital*
LCIA	-0.0160			
	(-0.97)			
LCIL		-0.0127		
		(-0.34)		
LCIO			-0.0251	
			(-0.71)	
LCI				-0.0201
				(-1.26)
Controls	YES	YES	YES	YES
Observations	3,621	3,621	3,621	3,621

Panel B: Pei et al. (2019) balancedness test

Dependent variable	(1) *Digital*	(2) *OBS*	(3) *LLP*	(4) *Subdebt*	(5) *Zscore*
Size	0.0674*	0.4113	-1.9339	-0.0729	2.4471
	(1.74)	(0.45)	(-1.08)	(-1.10)	(0.99)
OBS	0.0005				
	(0.23)				
LLP	0.0026				
	(0.75)				
Subdebt	-0.0041				
	(-0.45)				
Zscore	-0.0001				
	(-1.29)				
Digital		-0.2714	0.8689	-0.1317	-10.2875
		(-0.48)	(0.58)	(-0.48)	(-1.49)
Quarter FE	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES
Observations	3,621	3,621	3,621	3,621	3,621
R-squared	0.2835	0.8555	0.4013	0.6564	0.1662

Notes: Panel A reports Cox (1972) proportional hazard (Cox PH) model to verify that bank liquidity creation is exogenous with respect to digital acquisitions. Panel B reports results on balancedness test. Column 1 reports estimates of Equation (3). Columns 2-5 report tests for the balancedness in covariates (Pei et al., 2019) using control variables as the outcome variables and bank digitalization as the main explanatory variable. Variable definitions are provided in Table 1. All regressions include year and bank fixed effects. The standard errors are robust to heteroscedasticity and clustered at the state level. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 4: Digital banks, liquidity creation, and market share

Dependent variable	(1) *LCIA*	(2) *LCIL*	(3) *LCIO*	(4) *LCI*	(5) *Share*
Digital	-14.5212***	-0.7575	1.2080	-14.0707*	-0.2401*
	(-2.69)	(-0.19)	(0.89)	(-1.97)	(-1.96)
Size	5.7450***	-2.7035	-2.0293***	1.0122	0.3213***
	(3.07)	(-1.39)	(-3.05)	(0.35)	(3.60)
OBS	0.5010**	0.3158*	0.4243***	1.2412***	-0.0044
	(2.14)	(1.87)	(5.00)	(3.93)	(-1.00)
LLP	0.2967	0.0818	-0.0098	0.3687	0.0036
	(0.92)	(0.30)	(-0.14)	(0.69)	(0.72)
Subdebt	-0.2145	0.6085	0.1641	0.5581	0.0138
	(-0.92)	(1.41)	(1.56)	(1.62)	(1.27)
Zscore	-0.0076	-0.0082**	-0.0018	-0.0176***	-0.0000
	(-1.38)	(-2.11)	(-1.16)	(-2.86)	(-0.02)
Quarter FE	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES
Observations	3,621	3,621	3,621	3,621	3,621
R-squared	0.7815	0.7968	0.9290	0.7529	0.9796

Notes: This table reports estimates of Equation (1) using asset-side liquidity creation, liability-side liquidity creation, off-balance sheet liquidity creation, total liquidity creation, and market share as the outcome variables. Variable definitions are provided in Table 1. The standard errors are clustered at the bank level and the corresponding t-statistics are reported in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 5: Balance sheet composition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Loans			Deposits		
Dependent variable	*C&I*	*Consumer*	*Total*	*Saving*	*Demand*	*Time*	*Total*
Digital	-11.6868***	2.3080	-9.3788**	4.0266	0.4372	-16.6555***	-12.1917***
	(-2.97)	(0.95)	(-2.42)	(1.38)	(0.16)	(-4.40)	(-2.69)
Size	-1.4638	-1.2057	-2.6695	-1.2948*	-1.2304	-1.2314	-3.7566
	(-0.59)	(-1.07)	(-1.00)	(-1.98)	(-1.10)	(-0.48)	(-1.30)
OBS	0.8181***	0.0594	0.8775***	0.0823	0.0406	0.2739	0.3968
	(3.19)	(0.73)	(3.43)	(1.53)	(0.35)	(1.56)	(1.65)
LLP	0.6054	0.0597	0.6651	0.0271	0.0432	-0.0507	0.0196
	(1.50)	(0.70)	(1.58)	(0.47)	(0.27)	(-0.22)	(0.05)
Subdebt	0.5348	0.2992	0.8341*	0.1017	0.2211	0.6336	0.9564**
	(1.24)	(1.31)	(1.94)	(0.51)	(0.68)	(1.36)	(2.33)
Zscore	-0.0125*	-0.0020	-0.0145*	-0.0008	-0.0011	-0.0047	-0.0066
	(-1.77)	(-1.05)	(-1.89)	(-0.53)	(-0.29)	(-0.88)	(-1.26)
Quarter FE	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES
Observations	3,621	3,621	3,621	3,621	3,621	3,621	3,621
R-squared	0.8633	0.9377	0.7213	0.8829	0.7915	0.8460	0.7855

Notes: This table reports estimates of Equation (1) using C&I loans, consumer loans, total loans, saving deposits, demand deposits, time deposits, and total deposits as the outcome variables. Variable definitions are provided in Table 1. The standard errors are clustered at the bank level and the corresponding t-statistics are reported in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 6: Digital transformation and bank overheads

	(1) Small banks	(2) Large banks	(3) All sample
Dependent variable	*Overheads*	*Overheads*	*Overheads*
Small × Digital			58.1331**
			(2.45)
Digital	80.1783***	46.7930***	29.9605**
	(3.90)	(9.81)	(2.53)
Controls	YES	YES	YES
Quarter FE	YES	YES	YES
Bank FE	YES	YES	YES
Observations	360	3,261	3,621
R-squared	0.5830	0.4485	0.4444

Notes: This table reports estimates of Equation (1) using operating expenses to operating income, return on assets, and return on equity as the outcome variables. Variable definitions are provided in Table 1. The standard errors are clustered at the bank level and the corresponding t-statistics are reported in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 7: Lending and saving rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Loans			Deposits				Margin
Dependent variable	*C&I*	*Consumer*	*Total*	*Demand*	*Saving*	*Time*	*Total*	*NIM*
Digital	2.9315***	3.8658*	3.9080**	0.4309	0.8775***	0.1477	-0.3452	1.2294*
	(2.70)	(1.91)	(2.16)	(1.16)	(4.11)	(0.42)	(-0.89)	(1.87)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	3,621	3,621	3,621	3,621	3,621	3,621	3,621	3,621
R-squared	0.7142	0.7996	0.7604	0.7164	0.6507	0.5609	0.7676	0.7425

Notes: This table reports estimates of Equation (1) using C&I lending rate, consumer lending rate, total lending rate, saving deposit rate, demand deposit rate, time deposit rate, and total deposit rate as the outcome variables. Variable definitions are provided in Table 1. The standard errors are clustered at the bank level and the corresponding t-statistics are reported in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 8: Synthetic DID: Coefficient estimates and inferences

Dependent variable	(1) *LCIA*	(2) *LCIL*	(3) *LCIO*	(4) *LCI*
Digital	-7.8094***	3.0311*	0.0627	-5.3113*
	(-4.20)	(1.71)	(0.05)	(-1.85)
Quarter FE	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES
Observations	3,255	3,255	3,255	3,255

Notes: This table reports estimates of the average treatment effect (ATE) of digital acquisition on the outcome variables using synthetic DID estimation outlined by Arkhangelsky et al. (2021). Arkhangelsky et al. (2021) lay out three inference options for SDID estimation, namely bootstrap, jackknife, and placebo procedures. In our estimation, we use the placebo procedure that is more suitable for small number of treated units. This procedure randomly assigns placebo treatments based on the actual treatment structure to the control units (i.e., based on large-sample approximation). The standard errors are estimated using the placebo procedure based on 50 replications. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

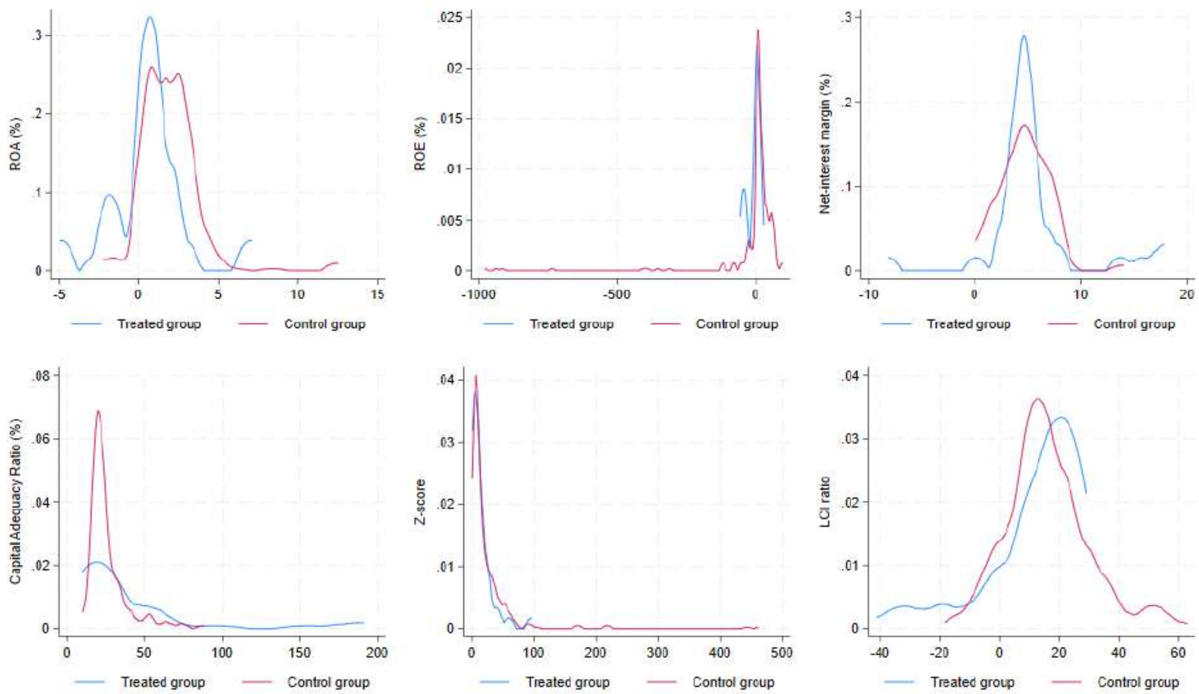
Table 9: Instrumental variable regressions

Dependent variable	(1) *LCIA*	(2) *LCIL*	(3) *LCIO*	(4) *LCI*
Digital	-13.5871*	-12.4165*	-1.1417	-27.1453***
	(-1.74)	(-1.89)	(-0.34)	(-2.73)
Controls	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES
First stage results				
Injection	0.0043***			
	(7.94)			
First-stage F-test	63.09			
Stock and Yogo maximal IV relative bias 10%	16.38			
Observations	3,621	3,621	3,621	3,621

Notes: This table reports instrumental variable estimates of Equation (1) using asset-side liquidity creation, liability-side liquidity creation, off-balance sheet liquidity creation, and total liquidity creation. The upper part of the table shows the second-stage results, while the lower part shows the first-stage results. We use the accumulated capital injection between six quarters and ten quarters prior to digital acquisition as an instrument. Variable definitions are provided in Table 1. The standard errors are clustered at the bank level and the corresponding t-statistics are reported in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

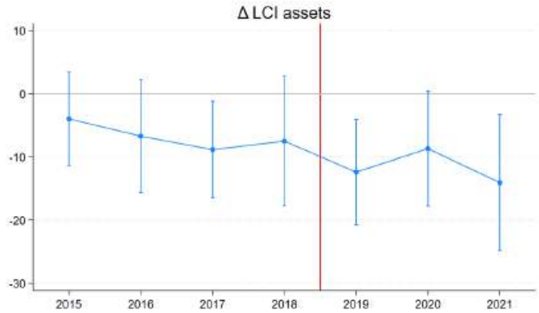
Figures

Figure 1: Kernel density estimates: Bank characteristics prior to digital transformation

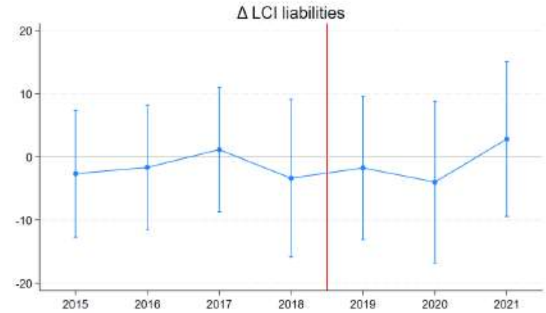


Notes: The figures illustrate the distribution of various bank characteristics for the treated and control groups using kernel density estimates in 2018, prior to the first occurrence of digital bank acquisition. The treated group refers to banks that experience digital transformation after 2018, and the control group depicts banks that retain their traditional business.

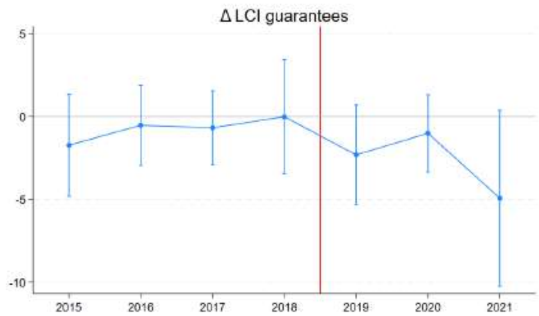
Figure 2: Parallel trends assumption



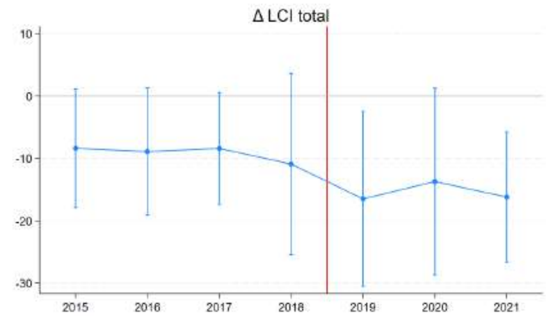
(a) Asset-liquidity creation



(b) Liability-liquidity creation



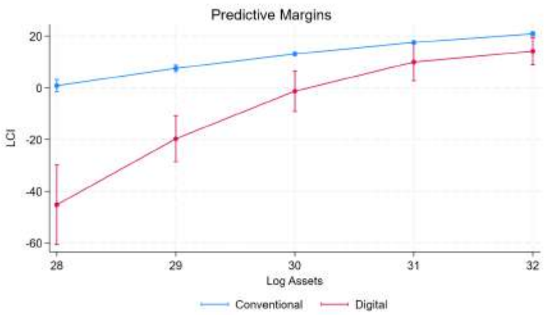
(c) OBS-liquidity creation



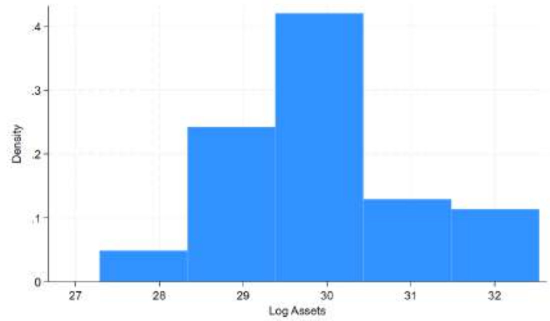
(d) Liquidity creation

Notes: This figure reports coefficient estimates and 90% confidence intervals of Equation (4) using asset-side liquidity creation, liability-side liquidity creation, off-balance sheet liquidity creation, and total liquidity creation as the outcome variables. The coefficients β_t show the quarterly average difference in the outcome variable between digital and traditional banks.

Figure 3: Interaction between bank size and liquidity creation



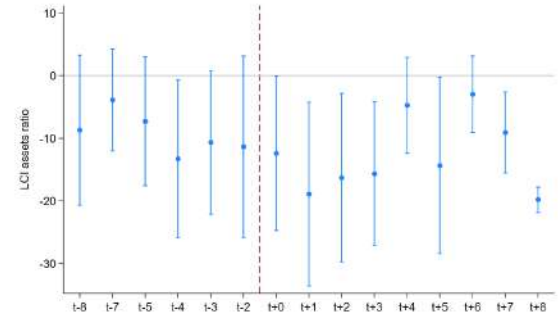
(a) Polynomial spline



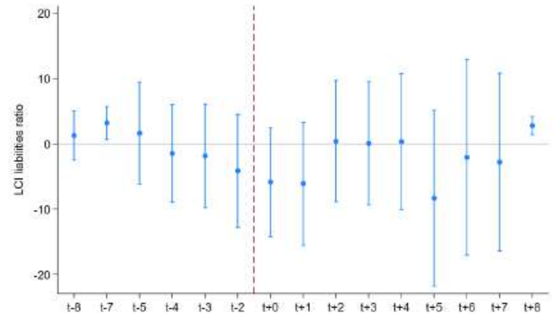
(b) Asset distribution of digital banks

Notes: Figure 3a illustrates nonparametric estimates using a polynomial spline of order 2. The nonparametric regression has two covariates bank size ($\mathbf{x}_{i,t}$) and digital bank dummy ($\mathbf{z}_{i,t}$), as estimate: $y_{i,t} = g(\mathbf{x}_{i,t}\mathbf{z}_{i,t}) + \epsilon_{i,t}$, where $E(y_{i,t}|\mathbf{x}_{i,t}\mathbf{z}_{i,t}) = g(\mathbf{x}_{i,t}\mathbf{z}_{i,t})$. A 2nd-order polynomial of $x_{i,t}$ and $z_{i,t}$ therefore would have terms $(x_{i,t}, z_{i,t}, x_{i,t}z_{i,t}, x_{i,t}^2, z_{i,t}^2, x_{i,t}^2 z_{i,t}^2)$. The 95% confidence intervals denoted by the vertical lines around each coefficient. Figure 3b illustrates the histogram of log assets within digital bank.

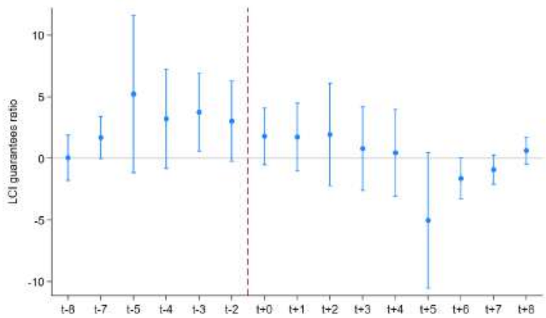
Figure 4: Interaction-weighted (IW) DID



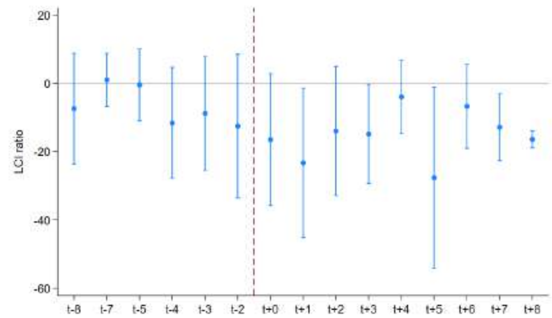
(a) Asset-liquidity creation



(b) Liability-liquidity creation



(c) OBS-liquidity creation



(d) Liquidity creation

Notes: The graph illustrates the estimated dynamic coefficients and 90% confidence intervals for the effects of digital acquisition on bank liquidity creation using an interaction-weigthed (IW) DID estimator. The dynamic coefficients show the quarterly average difference in the outcome variable between banks subject to a digital acquisition (the treatment group) and banks that are not (the control group). To create a balanced time horizon, following Sun and Abraham (2021), we exclude time periods $t < -8$ and $t > 8$. Appendix B.1 describes the IW-DID estimator methodology.

Online Appendix

A Additional information

Table A.1: M&A history in Indonesia

	All banks	Digital banks
Transaction		
Number of mergers	7 transactions	0 transaction
Number of acquisitions	21 transactions	9 transactions
Acquirer's business		
Holding company	6	2
Foreign bank	6	1
Domestic bank	13	3
Other NBFIs (including FinTech)	3	3
Acquisition length		
Mean	4.6 months	3.4 months
Median	2.0 months	3.0 months
Acquisition value		
Mean	\$1.1 billion	\$51 million
Median	\$695 million	\$38 million

Notes: This table documents the history of bank M&As in Indonesia between 2010 and 2022.

Table A.2: Definition of liquidity creation measures

Assets		
Illiquid assets (weight= 1/2)	Semiliquid assets (weight= 0)	Liquid assets (weight= −1/2)
Commercial and industrial loans	Residential real estate loans	Cash and due from other institutions
Other loans and financing receivables	Consumer loans	All securities (regardless of maturity)
Bankers' acceptances	Loans to depository institutions	Trading assets
Investment in unconsolidated subsidiaries		Reverse repurchased agreements
Intangible assets		
Fixed assets		
Other assets		
Liabilities		
Liquid liabilities (weight= 1/2)	Semiliquid liabilities (weight= 0)	Illiquid liabilities (weight= −1/2)
Transactions deposits	Time deposits	Bank's liability on bankers' acceptances
Savings deposits	Other borrowed money	Subordinated debt
Repurchased agreements		Other liabilities
Trading liabilities		Equity
Off-balance sheet guarantees		
Illiquid guarantees (weight= 1/2)	Semiliquid guarantees (weight= 0)	Liquid guarantees (weight= −1/2)
Unused commitments	Net credit derivatives	Net participations acquired
Net standby letters of credit	Net securities lent	Derivatives
Commercial and similar letters of credit		
All other off-balance sheet liabilities		

Notes: Berger and Bouwman (2009) liquidity creation measure ('cat fat' variation). $LC = 1/2 \times \textit{illiquid assets} - 1/2 \times \textit{liquid assets} + 1/2 \times \textit{liquid liabilities} - 1/2 \times \textit{illiquid liabilities} - 1/2 \times \textit{equity} + 1/2 \times \textit{illiquid guarantees} - 1/2 \times \textit{liquid guarantees} - 1/2\ \textit{liquidderivatives}$.

B Alternative DID Specifications

B.1 Interaction-weighted DID

Sun and Abraham (2021) proposes an interaction-weighted (IW) DID estimator that properly captures event studies with heterogeneous treatment effects. The estimator focuses on the weighted average of "cohort-specific average treatment effects on the treated" ($CATT$) for a particular event group e and their relative time periods l, and is robust to heterogeneous treatment effects across cohorts. In short, this method follows a three-step procedure.

The *first* step categorizes units into different cohorts based on their initial treatment timing. By designating the "never-treated" units as controls (C), the regression interacts relative time indicators with cohort indicators excluding indicators for the control group C, we then estimate:

$$\Delta y_{i,s,t} = \varphi_s + \varphi_t + \sum_{e \notin C} \sum_{l \neq -1} \tau_{e,l}(1\{E_i = e\} \cdot T^l_{s,t}) + \varepsilon_{i,s,t}, \tag{B.1}$$

where the coefficient estimator $\hat{\tau}_{s,l}$ from equation (B.1) is a DID estimator for $CATT_{e,l}$ with specific choices of pre-periods and control cohorts. The *second* step estimates the weights $Pr(E = e)$ by sample shares of each cohort in that period. The *third* step forms the IW estimator, which takes a weighted average of all estimates for $CATT_{e,l}$ from the first step and weight estimates from the second step. Formally, we estimate:

$$\hat{v}_g = \frac{1}{\mid g \mid} \sum_{l \notin g} \sum_{e} \hat{\tau}_{e,l}, \hat{Pr}(E_i = e | E_s \in [-l, L-l]) \tag{B.2}$$

where our DID estimator is:

$$\hat{\tau}_{e,l} = \frac{E_N[(y_{i,e+l} \cdot 1(E+i=e)]}{E_N(1 \cdot (E_i = e))} - \frac{E_N[Y_{i,e+l} \cdot 1(E_i \in C)]}{E_N(1 \cdot (E_i \in C} \tag{B.3}$$

B.2 Synthetic DID

Synthetic DID (SDID) outlined by Arkhangelsky et al. (2021) combines the strengths of traditional DID and SC. Similar to SC, SDID reweights and matches pre-treatment trends to reduce the reliance on parallel trend assumptions. Meanwhile, it is also similar to DID because it is invariant to additive unit-level shifts. SDID requires a balanced panel with N units and T *time* periods, as well as the binary treatment $W_{i,t} =\in \{0,1\}$. The first control units are never exposed to the treatmnet, while the last treated units are exposed after time T_{pre}. Similar to SC, SDID estimates weights $\hat{\omega}_i^{sdid}$ that align pre-treatment trends in the outcome of unexposed units with those for the exposed units, that is to say:

$$\sum_{i=1}^{N_{ctrl}} \hat{\omega}_i^{sdid} Y_{i,t} \approx N_{treat}^{-1} \sum_{i=N_{ctrl}+1}^{N} Y_{i,t} \tag{B.4}$$

for all $t = 1, ..., T_{pre}$. The method then estimates weights $\hat{\lambda}_t^{sdid}$, which balance the pre-treatment time periods with post-treatment ones. Next, these weights are used in a two-way fixed effects regression to estimate the average causal effect of the treatment (denoted by τ):

$$(\hat{\tau}^s did, \hat{\mu}, \hat{\alpha}, \hat{\beta}) = \underset{\tau,\mu,\alpha,\beta}{arg\,min} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{i,t} - \mu - \alpha_i - \beta_t - W_{i,t}\tau)^2 \hat{\omega}_i^{sdid} \hat{\lambda}_t^{sdid} \right\} \tag{B.5}$$

where the weights in the SDID estimator results in a "local" two-way fixed effect that emphasize units that on average are similar to the treated units in terms of their past, and periods that on average are similar to the treated periods.

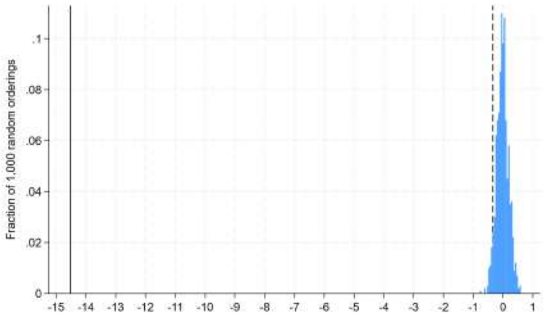
C Further robustness checks

Table C.1: Other balance sheet components

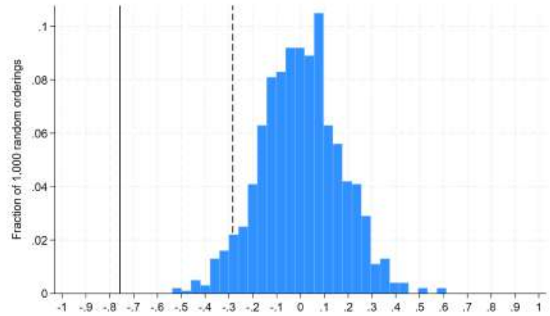
	(1)	(2)	(3)	(4)
Dependent variable	*Cash*	*Securities*	*Borrowings*	*Equity*
Digital	0.9972	9.4278**	-0.1520	13.1937**
	(0.49)	(2.48)	(-0.21)	(2.53)
Controls	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES
Observations	3,621	3,621	3,621	3,621
R-squared	0.6378	0.6210	0.7907	0.7624

Notes: This table reports estimates of Equation (1) using cash, total securities, total long-term borrowings, and total equity as the outcome variables. The standard errors are clustered at the bank level and the corresponding t-statistics are reported in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

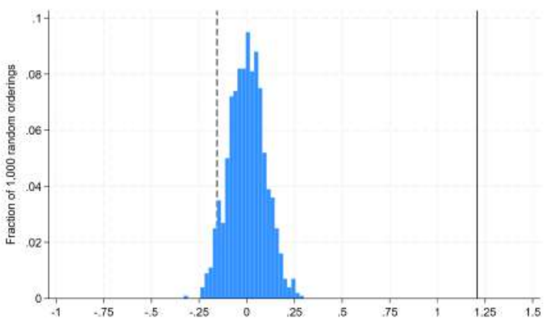
Figure C.1: Randomization inference



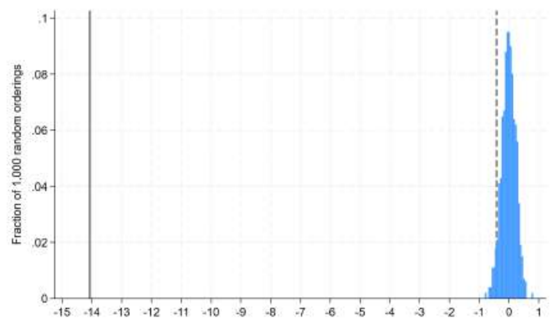
(a) Asset-liquidity creation



(b) Liability-liquidity creation



(c) OBS-liquidity creation



(d) Liquidity creation

Notes: This figure plots the permutation exercise following the method outlined by Conley and Taber (2011) to check the validity of the standard errors in DID settings using low number of treatment observations. The figure plots randomization inference based on 1,000 replications where the false treatment indicator is shuffled randomly across the control banks. The dashed lines indicate the bottom fifth percentile values of the placebo estimates, whereas the solid line shows the baseline estimate.

Table C.2: Anticipation effect, other acquisitions, and COVID-19

	(1)	(2)	(3)
Dependent variable	*LCI*	*LCI*	*LCI*
Anticipation	-9.7948		
	(-0.94)		
Acquisitions		-5.1675	
		(-1.58)	
Digital × COVID-19			28.2524
			(1.61)
Digital	-14.8585*	-14.3140**	-40.4937**
	(-1.91)	(-1.99)	(-2.11)
Controls	YES	YES	YES
Quarter FE	YES	YES	YES
Bank FE	YES	YES	YES
Observations	3,621	3,621	3,621
R-squared	0.7543	0.7541	0.7550

Notes: This table reports results of sensitivity tests. Column 1 shows estimates of Equation (1) by appending the model with an anticipation dummy. Column 2 shows estimates of Equation (1) by appending the model with non-digital acquisition dummy. Column 3 shows estimates of Equation (1) by appending the model with the interaction between digital bank and COVID-19 dummy. Variable definitions are provided in Table 1. The standard errors are clustered at the bank level and the corresponding t-statistics are reported in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table C.3: Market share of traditional banks

	(1)	(2)	(3)
Dependent variable	*Share*	*Share*	*Share*
Count	-0.0006	-0.0067	-0.0008
	(-0.13)	(-1.50)	(-0.19)
Size	0.3502***	0.2895***	0.4050***
	(3.44)	(4.02)	(3.19)
OBS	-0.0032	-0.0029	-0.0037
	(-0.67)	(-0.79)	(-0.71)
LLP	0.0067	-0.0144	0.0142**
	(1.22)	(-0.94)	(2.07)
Subdebt	0.0168	0.0163	0.0024
	(1.40)	(1.47)	(0.65)
Zscore	-0.0000	-0.0001	0.0001
	(-0.24)	(-0.68)	(0.57)
Quarter FE	YES	YES	YES
Bank FE	YES	YES	YES
Observations	3,422	2,358	1,106
R-squared	0.9796	0.9744	0.9976

Notes: This table reports the effect of digital acquisition on the market share of traditional banks. To do this, we restrict the sample to traditional banks and create *Count*, which counts the number of digital banks at time t. For example, in 2020Q4, there are 5 established digital banks, hence $Count = 5$. We then estimate $Share_{i,t} = \alpha + \beta \cdot Count_t + \gamma \cdot X_{i,t} + \phi_i + \phi_t + \epsilon_{i,t}$, where $Share_{i,t}$ is the market share of bank i at time t. Column 1 use all traditional bank observations as the sample. Column 2 use traditional banks with business focus on relationship banking only. Column 3 use matching traditional bank observations as the sample using log assets, OBS commitments, loan loss provisions, subordinated debt, and distance to default as the matching variables with caliper of 1%. Variable definitions are provided in Table 1. The standard errors are clustered at the bank level and the corresponding t-statistics are reported in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table C.4: Banks with similar size

Panel A: Banks with similar size

	(1)	(2)	(3)	(4)
Dependent variable	*LCIA*	*LCIL*	*LCIO*	*LCI*
Digital	-14.3324***	-0.9155	1.0294	-14.2185*
	(-2.65)	(-0.23)	(0.75)	(-1.98)
Controls	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES
Observations	3,072	3,072	3,072	3,072
R-squared	0.7655	0.7688	0.9270	0.7327

Panel B: KBMI 1 and 2

	(1)	(2)	(3)	(4)
Dependent variable	*LCIA*	*LCIL*	*LCIO*	*LCI*
Digital	-14.1265**	-0.8414	1.0590	-13.9090*
	(-2.60)	(-0.21)	(0.78)	(-1.92)
Controls	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES
Observations	3,037	3,037	3,037	3,037
R-squared	0.7610	0.7734	0.9268	0.6905

Panel C: Excluding KBMI 4

	(1)	(2)	(3)	(4)
Dependent variable	*LCIA*	*LCIL*	*LCIO*	*LCI*
Digital	-14.4090***	-0.7785	1.1707	-14.0168*
	(-2.66)	(-0.20)	(0.86)	(-1.96)
Controls	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES
Observations	3,481	3,481	3,481	3,481
R-squared	0.7727	0.7849	0.9289	0.7476

Notes: This table reports estimates of Equation (1) using asset-side liquidity creation, liability-side liquidity creation, off-balance sheet liquidity creation, total liquidity creation, and market share as the outcome variables. Panel A limits the sample to banks with similar size to digital banks. Panel B limits the sample to KBMI 1 and 2 banks. Panel C excludes KBMI 4 banks from the sample. Variable definitions are provided in Table 1. The standard errors are clustered at the bank level and the corresponding t-statistics are reported in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table C.5: Further sensitivity analysis

Panel A: Industry competitiveness

	(1)	(2)	(3)	(4)
Dependent variable	$LCIA$	$LCIL$	$LCIO$	LCI
$Digital$	-15.6541*	-9.0506***	-2.7471	-27.4519***
	(-1.91)	(-2.97)	(-1.35)	(-2.96)
$Digital \times NIM$	0.2662	1.6510**	0.7376**	2.6548***
	(0.36)	(2.52)	(2.39)	(3.85)
NIM	-0.1867	-0.1272	0.1467*	-0.1672
	(-0.54)	(-0.60)	(1.83)	(-0.40)
Controls	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES
Observations	3,621	3,621	3,621	3,621
R-squared	0.7818	0.8024	0.9312	0.7604

Panel B: No controls

	(1)	(2)	(3)	(4)
Dependent variable	$LCIA$	$LCIL$	$LCIO$	LCI
$Digital$	-12.3322**	-3.0085	-1.0072	-16.3479**
	(-2.62)	(-0.72)	(-0.51)	(-2.03)
Quarter FE	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES
Observations	3,621	3,621	3,621	3,621
R-squared	0.7606	0.7861	0.9148	0.7289

Notes: This table reports estimates of Equation (1) using asset-side liquidity creation, liability-side liquidity creation, off-balance sheet liquidity creation, total liquidity creation, and market share as the outcome variables. Panel A appends the model using the interaction between digital bank dummy and net interest margin. Panel B shows estimates without control variables. Variable definitions are provided in Table 1. The standard errors are clustered at the bank level and the corresponding t-statistics are reported in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

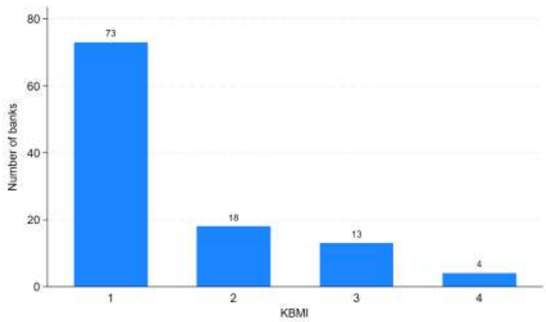
Table C.6: Oster (2019) Coefficient Stability

Panel A: No controls to all controls								
	QE controls		All controls		R^2_{max}		Bounding values	
Specification	$\dot{\beta}$	$\dot{R}^2$	$\tilde{\beta}$	$\tilde{R}^2$	$\Pi = 1.2$	$\Pi = 1.5$	$\beta^*_{\Pi=1.2}$	$\beta^*_{\Pi=1.5}$
$LCIA$	-10.5909	0.009	-14.5212	0.782	0.938	1.000	-15.3164	-15.6296
$LCIL$	-5.3932	0.003	-0.7576	0.797	0.956	1.000	0.1731	0.4276
$LCIO$	-3.4312	0.002	1.2080	0.929	1.000	1.000	1.5633	1.5633
LCI	-19.4152	0.022	-14.071	0.753	0.904	1.000	-12.9697	-12.2649

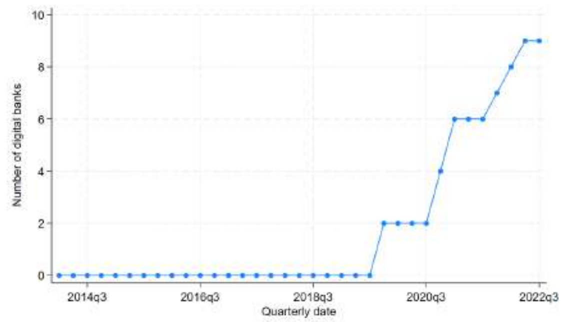
Notes: This table estimates bounding values for the baseline estimates following the procedure outlined by Oster (2019). The procedure assumes that selection on unobservables is proportional to selection on observables. The bounding value β^* is estimated as $\beta^* = \tilde{\beta} - \frac{(\dot{\beta}-\tilde{\beta})(R^2_{max}-\tilde{R}^2)}{\tilde{R}^2-\dot{R}^2}$, where $\dot{\beta}$ and $\dot{R}^2$ are the point estimate and R^2 for the regression without controls and $\tilde{\beta}$ and $\tilde{R}^2$ are the respective values from the regression with controls. The calculations assume that the degree of proportionality between selection on unobservables and selection on observables is one ($\delta = 1$). Since the procedure requires making an assumption about the maximum possible R^2, we follow Oster (2019) by using $R^2 = \min(1, \Pi \cdot \tilde{R}^2)$ with $\Pi = 1.2$ as our benchmark and our more conservative value of $\Pi = 1.5$.

D Additional figures

Figure D.1: Total number of Indonesian banks



(a) Number of banks by KBMI category



(b) Number of digital banks

Notes: Figure D.1a illustrates the distribution of Indonesian banks according to their KBMI category. Figure D.1b shows the growing number of digital banks in Indonesia between 2014 and 2022.