The dark side of bank digitalization: Bank liquidity creation and digital innovation failure*

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Abstract

The digitalization of financial services, including that of commercial banks, has seen a rapid proliferation in the recent years. I therefore examine how the creation of digital banks 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 (M&As). My results document that bank liquidity creation is lower after digital M&As relative to non-digital M&As. Further tests show that banks transformed into digital banks are smaller in size, limiting their capacity to quickly adopt and integrate new digital technology. This stumbling block undermines their business efficiency and market power, ultimately reducing liquidity creation. This evidence offers novel insights into the potential adverse effect of digital transformation in the banking sector.

JEL-Codes: G21, G34, O33.

Keywords: digital bank; bank liquidity creation; mergers and acquisitions; innovation failure.

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1 Introduction

The significant incorporation of digital innovations into the traditional banking model has driven bank digitalization, ultimately leading to the creation of full-fledged digital banks, a process referred to as digital transformation. Unlike traditional banks that only partially incorporate digital innovations, digital banks fully exploit digital innovations with no or limited reliance on brick-and-mortar outlets. Existing research shows that digital innovation in the banking sector improves bank performance and enables banks to create more liquidity in the economy (D'Andrea and Limodio, 2024; Scott et al., 2017; Silva et al., 2023). Digital innovation also minimizes geographic constraints and helps banks design tailor-made products to gain market share and capture the untapped market (Buchak et al., 2018; Choi and Loh, 2024; Herpfer et al., 2023).

Nevertheless, digital innovation is not without its risks. Theory suggests that innovation, including digital innovation, can result in a failure if firms lack factors such as financial capacity and operational capability to rapidly integrate the new technology (Baxter et al., 2023). For example, the beginning phase of digital innovation in the banking sector 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). A bank's lack of ability to smoothly undergo this process may lead to digital innovation failure. This risk is even higher within smaller banks that face higher levels of financial and operational constraints (Arza and López, 2021; Grandon and Pearson, 2004).

Given this backdrop, I aim to examine the effect of digital transformation on bank liquidity creation. In contrast to the impact of digital innovation on credit expansion within FinTechs that has been widely studied in the literature (Allen et al., 2022; Bao and Huang, 2021; Balyuk, 2023; Erel and Liebersohn, 2022), research that specifically focuses on full-fledged digital banks is still scarce. 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.

To tackle this issue, I exploit Indonesia's unique banking sector's regulatory environment to generate a plausibly exogenous variation in digital transformation status. Indonesian banking regulator, The Indonesian Financial Services Authority (OJK), actively aims to restructure and consolidate the industry by placing a regulatory barrier that significantly increases the cost of establishing new standalone banks while encouraging mergers and acquisitions (M&As) of smaller banks (Poczter, 2016; Shaban and James, 2018). Consequently, since the 1997 Asian Financial Crisis, practically new banks in Indonesia can only be established via M&As. In 2018, the OJK issued a regulation on digital services in the banking sector, which encourages investors with digital technology to convert traditional banks into digital banks. This new regulation has further focused the attention of the OJK's industry consolidation on M&As involving digital transformation (or digital M&As). 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; Pilloff, 2004). This setting allows me to use staggered difference-in-differences (DID) estimation to exploit bank variation over time in establishing new digital banks by comparing how the treatment group (digital M&As) responds to its new business model relative to a control group (non-digital M&As).

Using quarterly data of bank M&As in Indonesia between 2014 and 2022, I find that digital transformation decreases liquidity creation by 18.8 percentage points. When I decompose liquidity creation into asset-side, liability-side, and off-balance sheet dimensions, I find that both asset-side and liability-side liquidity creation drive digital banks' overall liquidity creation reduction. My econometric strategy revolves around staggered DID estimators, both standard, stacked, and semi-parametric, 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.

Why does digital transformation reduce liquidity creation? Prior research suggests that the adoption of new innovation always involves some degree of risk (Arza and López, 2021). If a bank is not equipped with the necessary capacity to adopt the new innovation, it becomes prone to innovation failure (Baxter et al., 2023). Our tests show that digital banks established via M&As tend to have smaller size and are less able to integrate the new technology efficiently. Instead of improving efficiency, the adoption of new technology increases digital banks' operational costs and reduces their market power. Because banks with weak market power are less likely to establish relationships with new clients, their capability to provide financial services and create liquidity is ultimately hampered (Cetorelli and Gambera, 2001; Petersen and Rajan, 1995).

My paper relates to two strands of literature. First, it builds on a growing number of studies that focus on innovation failure. In contrast to literature on innovation success, prior research assessing the determinants of innovation failure is still scarce (Pellegrino and Savona, 2017). Recently, however, attempts have been made to study this topic more extensively. For example, Baxter et al. (2023) conduct a systematic literature review based on a total of 69 peer-reviewed articles to redefine the concept of innovation failure and provide its theoretical underpinning. Arza and López (2021) study various obstacles that prevent innovation and reduce the intensity of investment in innovation in small firms. They find that cost, market, and institutional factors as the main obstacles to innovation, while market and knowledge factors tend to affect the intensity of investment in innovation. Different from these studies that focus on the roots of innovation failure, a novel contribution of our paper is to show the consequences of innovation failure in the banking sector.

Another growing strand of literature studies the effects of digital innovations in the financial sector. Evidence demonstrates how the spread of FinTechs can fill the credit gap (Allen et al., 2022; Balyuk, 2023). Growing digital credit also positively contributes to entrepreneurship and financial inclusion, particularly in disadvantaged areas (Erel and

Liebersohn, 2022). Unlike these articles that show the positive effects of digital innovations within FinTechs, my work speaks to the risk of innovation failure when a firm lacks the ability to incorporate new technology. My research is closest to that of Fuentelsaz et al. (2012), which finds no significant relationship between technological diffusion, represented by the introduction of the Automated Teller Machine in Spanish banks, and bank performance when the technology is highly imitable and does not improve competitive advantage. Instead of focusing on technological imitability, I examine the potential unintended consequences of digital innovation on bank intermediary functions.

My 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 (D'Andrea and Limodio, 2024; Scott et al., 2017; Silva et al., 2023). 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 and adopt the technology efficiently (Feyen et al., 2021; OJK, 2021). Many digital banks also have poor risk management, which increases their operating costs and hampers their financial intermediary functions (Koont et al., 2023). My findings therefore provide new evidence where innovation failure can diminish the benefits of digital transformation, and how this affects liquidity creation.

The paper is organized as follows. Section 2 provides the overview of Indonesian banking sector and presents my conceptual framework. In Section 3, I show data sources, descriptive statistics, and outline the empirical model. I report my baseline results in Section 4. Section 5 discusses my robustness checks, while Section 6 concludes.

2 Literature review

2.1 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). 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).[1] Because of their limited capacity, small banks are unable to grow and compete with large banks while simultaneously imposing additional risk to the financial system due to their substandard risk management procedure.

This situation prompts the OJK to consolidate the banking sector and reduce the number of smaller banks due to their inefficiency (Shaban and James, 2018). The OJK therefore puts barriers to entry by requiring minimum paid-in capital of Rp3 trillion ($\approx$ \$200 million) to establish a new standalone bank, while the majority of the existing banks still have paid-in capital significantly below that figure.[2] Since the cost of establishing a new bank is too high, no new standalone banks were ever established since the 1997 Asian Financial Crisis. Instead, the OJK pushes 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 the M&As are driven by a regulatory pressure, they are usually completed relatively quickly and not intended for shareholder value maximization (Berger et al., 1999; Chen and Vashishtha, 2017; Shaban et al., 2014).[3]

[1] 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 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.

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

[3] Many small- and medium-sized banks in Indonesia have similar business characteristics and performance.

As shown by Panel A of Table 1, the median of M&A processes in Indonesia is 3.0 months, with an average of 6.2 months.

[Insert Table 1]

In 2018, the OJK issued a regulation on digital services in the banking sector, which marked the beginning of the establishment of full-fledged digital banks in Indonesia. The issuance of the regulation was accompanied by a blueprint that encouraged aspiring investors with digital bank technology to convert Indonesian traditional banks into digital banks (OJK, 2021). This implies that the speed of digital transformation and the availability of investors with digital bank technology become the two most crucial factors in influencing digital M&As, while the performance of the banks become less relevant. This is confirmed by Panel C of Table 1 that compares main performance indicators of banks with digital M&As and non-digital M&As prior to the M&As. The mean-comparison results find no significant difference in performance between the two groups. Appendix Figure B.1 displays more data and information associated with the evolution of digital banks in Indonesia. From these data, it can be inferred that it is unlikely for digital M&As to be driven or influenced by banks' ex-ante business performance. The absence of simultaneous relationship between digital M&As and liquidity creation therefore enables me to identify the causal effect of digital M&As on liquidity creation. I discuss about this issue in more detail in Section 3.

2.2 Conceptual framework

Theoretical model suggests that innovation within financial institutions enhances efficiency and bank intermediary functions (Boot and Thakor, 2000). More recent empirical works

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.

that focus on digital innovation is generally consistent with this conjecture. Specific digital adoptions by a financial institution such as the introduction of high-speed internet, the standards for worldwide interbank financial telecommunication (SWIFT), and the real-time gross settlement system (RTGS) are positively correlated with higher efficiency, improved profitability, increased lending, and higher stock market returns (D'Andrea and Limodio, 2024; Scott et al., 2017; Silva et al., 2023). Additionally, digital innovations enable financial institutions to capture untapped markets by improving loan access for marginal firms and borrowers from more remote areas, thereby creating liquidity in the economy and enhancing financial inclusion (Allen et al., 2022; Erel and Liebersohn, 2022; Herpfer et al., 2023). When a bank becomes a full-fledged digital bank, it adopts most, if not all, aspects of digital innovation and is more likely to maximize its impact on operating efficiency and liquidity creation capability.

Despite its potential benefits, innovation in the banking sector, such as digital transformation, is not immune to the risk of failure. Theory suggests that factors such as technological, market, financial, operational, and organizational risks may contribute to innovation failure (Baxter et al., 2023). Adopting a new innovation involves a high willingness to take on risk or technical uncertainty that may be harmful to firm performance (Arza and López, 2021). For example, when a bank is undergoing a digital transformation, it needs to take risk by investing high initial fixed costs associated with digital infrastructure (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. Banks also risk overspending by investing in unnecessary technology (OJK, 2021). To prevent innovation failure, a bank needs to ensure that the benefits of acquiring digital innovation outweigh the costs. For example, banks can minimize the investment costs by amortizing them over a large customer base (Feyen et al., 2021).

Even though both large and small firms face similar risks in pursuing innovation, the consequences are often more severe for smaller firms (Arza and López, 2021; Grandon and

Pearson, 2004). When investing in digital infrastructure during digital transformation, smaller banks may not have the ability to amortize the investment costs due to their smaller customer base. Additionally, while large banks have the capacity to hire experts to address capability gaps and minimize integration disruptions, smaller banks may lack the resources to afford such luxuries. This makes them more likely to encounter stumbling blocks during the transition process, ultimately curtailing the benefits of acquiring new technology (Scott et al., 2017). Under the worst-case scenario, slow integration process and sustained costly transition may increase operational costs and reduce efficiency, eventually reducing market power because the market is dominated by more efficient banks (González, 2009; Koetter et al., 2012; Maudos and de Guevara, 2007). Decreased market power diminishes incentives for banks to establish long-term relationships with new clients, particularly younger firms, thus reducing liquidity creation (Cetorelli and Gambera, 2001; Petersen and Rajan, 1995). In contrast, banks with stronger market power are more likely to expand and provide financial services to new clients, leading to higher liquidity creation.

[Insert Figure 1]

Figure 1 visualizes my conceptual framework. When digital innovation is successful, it improves bank efficiency that ultimately increases market power and bank liquidity creation. In contrast, digital innovation failure increases bank operating costs, undermining market power and reducing their liquidity creation capability.

3 Empirical design

3.1 Outcome variables

The key dependent variables in the empirical analysis measure bank liquidity creation, market power index, and various balance sheet as well as income statement items. I discuss the construction of each in turn.

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

To measure liquidity creation, I use the Berger and Bouwman (2009) liquidity creation index. This index can be decomposed into on- and off-balance sheet components, which allows us to examine which aspects of balance sheet drive the evolution of liquidity creation after digital M&As.

[Insert Table 2]

Berger and Bouwman (2009) provides four versions to measure liquidity creation. In this paper, I 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').[4] Prior research prefers this variant because loan 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). Table 2 provides details of the construction of liquidity creation index.

3.1.2 Lerner index

My conceptual framework suggests that innovation failure decreases liquidity creation via bank market power reduction. To measure bank market power, I follow previous research by using the Lerner index (*Lerner*) that approximates banks' ability to extract rents and set prices above marginal costs (Anginer et al., 2014; Koetter et al., 2012). The Lerner index is calculated using a two-step procedure. The first step uses bank-level data to

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

estimate its log-cost function:

$$\begin{aligned}\log C_{i,t} = \alpha + \beta_1 \log A_{i,t} + \beta_2 \log A_{i,t}^2 + \beta_3 \log I_{i,t} + \beta_4 \log P_{i,t} + \beta_5 \log O_{i,t} + \beta_6 \log A_{i,t} \cdot \log I_{i,t} \\ + \beta_7 \log A_{i,t} \cdot \log P_{i,t} + \beta_8 \log A_{i,t} \cdot \log O_{i,t} + \beta_9 \log I_{i,t}^2 + \beta_{10} \log P_{i,t}^2 + \beta_{11} \log O_{i,t}^2 \\ + \beta_{12} \log I_{i,t} \cdot \log P_{i,t} + \beta_{13} \log I_{i,t} \cdot \log O_{i,t} + \beta_{14} \log P_{i,t} \cdot \log O_{i,t} + \gamma_t + \varepsilon_{i,t},\end{aligned} \tag{1}$$

where $C_{i,t}$ is total costs and is equal to the sum of interest and non-interest expenses; $A_{i,t}$ is total assets; $I_{i,t}$ is the ratio of interest expenses to total assets; $P_{i,t}$ denotes the ratio of personnel expenses to total assets; and $O_{i,t}$ is the ratio of other operating expenses divided by total assets; γ_t are quarter fixed effects; and $\varepsilon_{i,t}$ is the error term. The subscripts i and t denote each bank and year respectively.

Next, I impose five restrictions on regression coefficients in Equation (1) to attain homogeneity of degree one in input prices:

$$\begin{aligned}\beta_3 + \beta_4 + \beta_5 &= 1, \\ \beta_6 + \beta_7 + \beta_8 &= 0, \\ \beta_9 + \beta_{12} + \beta_{13} &= 0, \\ \beta_{10} + \beta_{12} + \beta_{14} &= 0, \\ \beta_{11} + \beta_{13} + \beta_{14} &= 0.\end{aligned}$$

In the second step, I estimate the marginal costs for each bank using the estimated parameters from Equation (1):

$$\begin{aligned}MC_{i,t} &= \frac{\partial C_{i,t}}{\partial A_{i,t}} \\ &= \frac{C_{i,t}}{A_{i,t}} \cdot [\beta_1 + 2\beta_2 \log A_{i,t} + \beta_6 \log I_{i,t} + \beta_7 \log P_{i,t} + \beta_8 \log O_{i,t}].\end{aligned}$$

The Lerner index is then computed as:

$$Lerner_{i,t} = \frac{R_{i,t} - MC_{i,t}}{R_{i,t}}, \tag{2}$$

where $R_{i,t}$ is total revenues divided by total assets for bank i at time t.

3.1.3 Other balance sheet and income statement items

I also use various bank balance-sheet and income statement items as the dependent variables to complement my baseline analysis. Specifically, I use operating costs to operating income ($Costs$), loan loss provisions to assets (LLP), non-performing loans to assets (NPL), C&I loans to assets ($C\&I\ loans$), consumer loans to assets ($Consumer\ loans$), total loans to assets ($Total\ loans$), saving deposits to assets ($Saving\ deposits$), demand deposits to assets ($Demand\ deposits$), time deposits to assets ($Time\ deposits$), and total deposits to assets ($Total\ deposits$).

3.2 Data and descriptive statistics

To construct my base sample, I draw data from individual banks' financial reports that span from 2014Q1 to 2022Q4. I then identify and keep 23 banks that experienced M&As throughout this sample period, comprising of 9 digital M&As (treated banks) and 14 non-digital M&As (control banks). This procedure produces 300 treated observations and 408 control observations with a total of 708 observations. Table 3 provides the description of each variable in the data set.

[Insert Table 3] [Insert Table 4]

Table 4 reports the summary statistics of the variables used in the empirical analysis. The average liquidity creation, LCI, is 11.2%. When I deconstruct liquidity creation measure into asset-side ($LCIA$), liability-side ($LCIL$), and off-balance sheet ($LCIO$), the averages are 14.6%, -10.2%, and 6.8%, 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.

3.3 Econometric specification

Similar to prior research in M&A literature (Chen and Vashishtha, 2017; Chu, 2021; Liebersohn, 2024), I estimate a staggered DID model to quantify the effects of digital M&As. 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. The treated group consists of digital M&As, while the control group comprises of non-digital M&As. Specifically I estimate:

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

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 converted into a digital bank after the M&A 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. We define a digital banks as a bank that provides and carries out business activities primarily through electronic channels without a physical office other than the head office or using limited physical offices, which is in line with the OJK's guideline. Following existing banking as well as M&A literature (Chen and Vashishtha, 2017; Nguyen et al., 2020; Raz, 2023), my control variables include log assets ($Size$), non-performing loans to assets (NPL), subordinated debt to assets (*Subdebt*), z-score or distance to default ($Zscore$), and derivative transactions to assets ($Derivatives$). The standard errors are clustered at the bank level.

The coefficient *Digial* represents the average causal effect of digital M&As on bank liquidity creation. Following prior research, I assume the timing of digital M&As is exogenous in the sense that they are not driven by bank performance (Berger et al., 1999; Chen and Vashishtha, 2017; Pilloff, 2004).[5] Despite this, identifying a causal relation running

[5]Following Calderon and Schaeck (2016), I perform Cox (1972) proportional hazard tests by estimating the conditional probability of digital M&As to ensure that my empirical model is not threatened by the presence of simultaneity bias. The results in Appendix Table A.1 confirm that digital M&As do not depend on bank liquidity creation.

from digital M&As to liquidity creation is still challenging, owing to the possible presence of unobserved characteristics that are correlated with both digital M&As and liquidity creation.

[Insert Table 5]

The first solution to this concern is to include bank and quarter fixed effects. Bank fixed effects control time-invariant bank-specific characteristics that affect liquidity creation, while quarter fixed effects control for quarterly shocks common to all banks in my sample such as the effect of the COVID-19 pandemic. The second solution is to experiment with different specifications in terms of control variables to ensure that my main empirical specification does not suffer from a "bad-controls" phenomenon. I also check the stability of the coefficient of interest using Oster (2019) coefficient stability test. Section 5 discusses this issue in more detail. Finally, I perform balancedness test outlined by Pei et al. (2019) to ensure that digital M&As are not systematically correlated with the control variables. To conduct the test, I first regress digital M&A dummy on the control variables:

$$Digital_{i,t} = \theta X_{i,t} + \phi_i + \phi_t + \epsilon_{i,t}, \tag{4}$$

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

4 Results

4.1 Main findings

Table 6 reports estimates of Equation (3). Column 1 shows the effect of digital transformation on bank liquidity creation. The coefficient of interest shows liquidity creation falls by 18.8 percentage points and this is significant at 1%. This implies that digital M&As lead to significantly lower liquidity creation relative to non-digital M&As. In the remaining columns of Table 6, I break down total liquidity creation into asset-side, liability-side and off-balance sheet liquidity creation. In column 2, I find that digital M&As significantly reduce asset-side liquidity creation by 10.5 percentage points. Column 3 indicates that digital M&As result in a significantly lower liability-side liquidity creation, by 8.1 percentage points. Meanwhile, column 4 suggests no significant impact of the coefficient of interest on off-balance sheet liquidity creation despite the negative relationship. Together, these findings imply that digital M&As reduce total liquidity creation through bank balance sheet, while bank off-balance sheet is less affected by the shock.

[Insert Table 6]

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. Non-performing loans are positively correlated with total and asset-side liquidity creation, while negatively correlated with off-balance sheet liquidity creation. Subordinated debt is only negatively correlated with liability-side liquidity creation and z-score has a negative relationship with total and asset-side liquidity creation. In contrast, there is a positive correlation between derivative transactions and liability-side as well as off-balance sheet liquidity creation.

Next, I conduct an event study analysis to inspect the parallel trend assumption and understand the dynamic effects of the treatment by estimating the following:

$$y_{i,t} = \phi_i + \phi_t + \beta \cdot \sum_{t<-8} T_{i,t}^q + \sum_{q=-8}^{-2} \mu_q T_{i,t}^q + \sum_{q=0}^{8} \mu_q T_{i,t}^q + \gamma \cdot \sum_{t>8} T_{i,t}^q + \epsilon_{i,t} \tag{5}$$

where $T_{i,t}^q$ indicates a dummy equal to one for treatment bank i being q periods away from initial treatment at time t, and zero otherwise. In the specification, I bin distant relative periods prior and after digital M&As, i.e., $t > 8$ and $t < -8$, to differentiate between the short-term effects and long-term effects. I also drop the time period $t = -1$ to avoid perfect multicollinearity. Equation (5) is estimated using two-way fixed effects estimator (TWFE). The consistency of my TWFE estimator relies on the standard "common trends" assumption. However, recent econometric literature suggests that this assumption is often implausible because, in my setting, it is possible that digital M&As have a heterogenous effect (Baker et al., 2022; Sun and Abraham, 2021). For example, the effect of the shock during the COVID-19 pandemic on liquidity creation may be different from that in other periods. I therefore follow the most recent eceonometric literature by complementing my TWFE estimator with a stacked DID estimator (Baker et al., 2022; Cengiz et al., 2019). Stacked DID estimator creates a separate event-specific dataset for each valid sub-experiment. Then, these event-specific datasets are stacked together, and a TWFE-DID regression is estimated on the stacked dataset by incorporating dataset-specific bank and time fixed effects. The objective is to estimate an average causal effect by fitting the TWFE-DID regressions to the stacked dataset.

[Insert Figure 2]

Figure 2 plots the event study graph showing the changes of bank liquidity creation in the treated and control banks relative to digital M&A quarters. Panel (a) illustrates the results of the TWFE-DID estimator, while panel (b) exhibits that of the stacked DID approach. In panel (a), the dynamic coefficient estimates are insignificant prior to digital M&As. These results imply that the control banks provide an accurate depiction of the trend of liquidity creation among the treated banks in the absence of digital M&As. In other words, this evidence suggests that the baseline results are unlikely to be driven by nonparallel trends between treated and control firms. In the first quarter after digital M&As, bank liquidity creation falls in the treatment group relative to the control group. Even though the effect of the M&As diminishes in most of the subsequent quarters, the long-run effect (eight quarters or two years after digital M&As) remains negative and statistically significant, corroborating my baseline results. The stacked DID results in panel (b) further support these findings.

4.2 Size heterogeneity

My conceptual framework shows that the risk of innovation failure is higher for smaller banks because they are less likely to efficiently adopt, integrate, and implement new technology, as well as amortize the investment costs, which ultimately undermines their liquidity creation. I therefore test the role of bank size in influencing the effect of digital M&As on liquidity creation.

My test examines 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, I perform non-parametric estimation using polynomial splines of order 2.[6] I visualize the results by estimating the predictive margins with 95% confidence intervals for digital banks and other banks. Panel (a) of Figure 3 graphically presents the econometric results of this test.

[Insert Figure 3]

I can draw two inferences from the figure. First, it shows heterogeneous effects across the bank size distribution. The effect of size on liquidity creation increases as banks

[6] My 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 $(x_{i,t}, z_{i,t}, x_{i,t}z_{i,t}, x_{i,t}^2, z_{i,t}^2, x_{i,t}^2 z_{i,t}^2)$.

become larger. 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 for banks with non-digital M&As. Banks with digital M&As need 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 banks with non-digital M&As 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. Smaller banks also have the tendency to over-invest in new technology instead of carefully allocatge their limited resources (OJK, 2021). Because fixed costs depend less on bank size, banks need to be sufficiently large to be able to fully benefit from digital transformation. Panel (b) of Figure 3 illustrates the histogram of log assets within digital banks and confirms that a considerable number of digital banks do not have assets above the minimum threshold (or the capacity to achieve economies of scale) to positively create liquidity.

4.3 Transmission mechanism: Bank efficiency and market power

Next, I discuss how digital M&As can decrease liquidity creation by undermining bank efficiency and market power. Following prior research, I measure bank efficiency and market power using the ratio of operating costs to operating income and the Lerner index, respectively (Anginer et al., 2014; Koetter et al., 2012; Saka et al., 2022). I then estimate Equation (3) using these variables as the outcome variables. To incorporate the role of bank size, I also divide the sample into small and non-small banks based on the threshold I obtain from Figure 3 (i.e., log assets=30).

[Insert Table 7]

Table 7 presents the results. Columns 1-3 of Table 7 display the results using the ratio of operating costs to operating income as the dependent variable. In column 1, the coefficient of interest is positive and significant at the 1% level, indicating that digital M&As increase banks' operating costs by 42.7 percentage points (or 43.7%, considering the sample average of 97.8%). Column 2 shows the estimates for small banks (i.e., log assets<30). The results show a positive and significant correlation between digital M&As and the ratio of operating costs to operating income within small banks. The magnitude of 93.7 percentage points suggests that the operating costs ratio of small banks increase by 95.8% after digital M&As, more than twice than the sample average. This evidence is also in line with my conceptual framework and prior findings, which argues that small banks are more vulnerable to innovation value due to their limited capacity to exploit economies of scale. Finally, my results in column 3 imply that digital M&As significantly increase operating costs by 43.6 percentage points (44.5%) within medium and large banks (i.e., log assets≥30).

The remaining columns show the impact of digital M&As on the Lerner index. Column 4 shows that digital M&As significantly reduce the Lerner index by 3.3 percentage points by using all banks as the sample. Considering the average Lerner index of 8.9, this is equivalent to a 37.1% decrease. When I split the sample, the results for small banks in column 5 shows a negative and significant relationship between digital M&As and the Lerner index, validating further my finding in column 2. Specifically, this evidence implies that digital M&As reduce the Lerner index by 46.1% within small banks. In contrast, the estimated coefficient in column 6 is insignificant despite the negative sign. This evidence suggests that digital M&As have no significant effect on the market power of medium and large banks.

The key message emanating from Table 7 is that the liquidity creation reducing effects of digital M&As are due to changes in bank efficiency and market power. The adoption of new innovation involves various risks that can affect a firm's cost structure and efficiency (Baxter et al., 2023). If a bank cannot overcome these risks and incorporate the new innovation, it is more likely to experience innovation failure and suffer higher operating costs as well as lower efficiency. When a bank is inefficient, it is more likely to be outcompeted by more efficient banks and lose market power (González, 2009; Maudos and de Guevara, 2007). As a bank loses its market power, it avoids establishing long-term relationships with new clients at the expense of having lower liquidity creation (Petersen and Rajan, 1995). Further examination shows that these reducing effects are more pronounced within smaller banks. This evidence is consistent with the argument in Arza and López (2021) that smaller firms tend to find more obstacles in adopting new innovation.

4.4 Digital transformation and credit risk

Literature suggests that digital lending providers, i.e., loans provided by FinTechs and digital banks, tend to have higher credit risk owing to their likelihood to have sub-prime borrowers (Bao and Huang, 2021; Koont et al., 2023). In response, banks may need to decelerate their loans growth, thus reducing liquidity creation (Beyhaghi et al., 2017; Park and Shin, 2021). This suggests a possibility of digital banks reducing liquidity creation to avoid higher non-performing loans rather than due to having efficiency and market power constraints.

[Insert Table 8]

To test this potential confound, I estimate Equation (3) using non-performing loans and loan loss provisions as the outcome variable, respectively. The results in columns 1 and 2 of Table 8 indicate that my coefficient of interest does not have a significant impact on these variables. This suggests that digital M&As do not lead to higher credit risk, represented by either non-performing loans or loan loss provisions. Additionally, I create NPL^{hi} and LLP^{hi}, which are dummy variables equal to one if a bank's non-performing loans or loan loss provisions are higher than the industry's median in quarter t. I then interact the digital M&As dummy with these dummy variables, and amend Equation (3) by including this interaction term. Columns 3 and 4 of Table 8 show that none of the interaction variables have a significant effect on liquidity creation. Meanwhile, the effect of digital M&As remains negative and statistically significant in both regressions. These findings confirm that credit risk is not a confounding factor that influences the effect of digital M&As on liquidity creation.

4.5 Impact on loans and deposits

My baseline findings show that digital M&As reduce the asset-side and liability-side liquidity creation. To see the dynamics within each side of the balance sheet, I examine the impact of digital M&As on loans and deposits, the largest contributors to bank assets and liabilities, respectively. In columns 1-3 of Table 9, I estimate Equation (3) using C&I loans, consumer loans, and total loans, respectively, as the outcome variables. In column 1 of the table, I find digital M&As significantly decrease the share of C&I loans to assets by 11.3 percentage points. Based on the 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 6) is similar to that C&I regression (Column 2 of Table 9). Column 2 of Table 9 reports estimates of Equation (3) using consumer loans to assets as the dependent variable. The variable of interest, however, is statistically insignificant. Finally, column 3 of the table presents the effect of digital M&As on total loans to assets. The estimated coefficient is negative and significant at the 1% level. Economically, the estimates show the treated banks' total loans to assets decline by 12.1 percentage points relative to the control banks.

[Insert Table 9]

Now I turn my discussion to bank deposits. Columns 4-7 of Table 9 present estimates of Equation (3) using saving deposits, demand deposits, time deposits, and total deposits, respectively, as the dependent variables. In columns 4 and 5 of Table 9, the coefficients of interest are statistically insignificant. Both saving deposits and demand deposits appear invariant to digital transformation. Column 6 of Table 9, however, shows a 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. In column 7 of Table 9, I find that digital transformation significantly decreases total deposits to assets by 20.3 percentage points.[7]

4.6 Alternative specification: Semi-parametric DID

One of the main challenges of my empirical identification is to ensure that it addresses the imbalances in the characteristics of digital and non-digital M&As. Under this condition, the parallel trend assumption may be implausible. To resolve this issue, the average bank characteristics prior to M&As need to be balanced across the groups. I do this by re-estimating my baseline model using semi-parametric difference-in-difference (SDID) estimator outlined by Abadie (2005). SDID follows a two-step procedure. First, it estimates the propensity score using a set of covariates used in the baseline model. Then, it reweights the sample using the calculated propensity score to construct the SDID sample. Observations with propensity scores greater than 0.99 and less than 0.01 are excluded from the sample to create a more balanced comparison. The rebalanced sample drops to 396 observations from the original 708 observations.

[Insert Table 10]

The estimates in Table 10 support the earlier difference-in-difference results. Column 1 shows that following digital M&As, liquidity creation is significantly lower by 14.6 percent-

[7]As shown in Online Appendix Table A.2, further investigation reveals that the reduction in liability-side liquidity creation is mainly driven by increased equity. Meanwhile, digital M&As have no significant effect on other short-term assets such as cash equivalents and securities, as well as other long-term liabilities such as long-term borrowings.

age points. In column 2, the coefficient of interest is negative and significant, indicating that asset-side liquidity creation is 5.2 percentage points lower after digital M&As. Column 3 also shows a negative and significant increase in liability-side liquidity creation after digital M&As. Finally, column 4 shows that the effect of digital M&As becomes significant on off-balance sheet liquidity creation.

5 Robustness checks

I conduct sensitivity tests and further robustness checks to ensure that my main findings are robust and not driven by unobservable confounds.

First, I re-estimate Equation (3) without control variables to ensure that the findings are not due to a 'bad-controls' phenomenon. The result in column 1 of Appendix Table A.3 shows that the coefficient of interest is similar in economic magnitude and statistical significance to the baseline findings. I also rule out a series of potential omitted variables. My sample period covered the COVID-19 pandemic. To ensure that this factor does not confound my main findings, I interact my coefficient of interest with a COVID-19 dummy. Column 2 of Appendix Table A.3 affirms that the results are driven by the COVID-19 pandemic. Prior research shows that bank liquidity creation changes over the business cycle (Flannery et al., 2022). The estimates in Column 3 of Appendix Table A.3 affirms the robustness of my findings to controlling for macroeconomic conditions, i.e. GDP growth. During the sample period, the central bank changed its policy rate several times. I therefore interact digital M&As with a dummy equal to one if the central bank changes its policy during the quarter and zero otherwise. Column 4 of Appendix Table A.3 shows that my results are robust to this change.

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. I complement my 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 A.4 highlights that the bounds for my main outcome variables exclude zero and confirm the robustness of my baseline findings.

DID estimator uses potentially serially correlated long time series that may lead to inconsistent inferences (Bertrand et al., 2004). We resolve this issue by block bootstrap the standard errors as outlined by Bertrand et al. (2004). Our findings in Online Appendix Table A.5 demonstrate the results are robust.

6 Conclusions

The digitalization of financial institutions have become one of the fasting growing topics in finance literature. While existing research focuses on its benefits, digital innovation is not without risks. In this paper, I leverage Indonesia's unique regulatory framework to study how the risks associated with digital innovation can negatively affect banks' intermediary functions.

My baseline findings suggest that digital transformation, represented by digital M&As, significantly reduce bank liquidity creation. The decrease is primarily driven by on-balance sheet items rather than off-balance sheet items. Next, I discuss the possible mechanism in which digital M&As potentially reduce liquidity creation. My conceptual framework suggests the presence of innovation failure risk where banks face technical uncertainty and are financially, operationally, and/or organizationally unequipped to adopt new innovation. Our tests show that such unreadiness reduces efficiency and market power, leading to lower liquidity creation. Further examination reveals that this risk is more pronounced in smaller banks. Finally, my results are robust to various sensitivity checks and alternative econometric specifications.

My findings provide novel insights into the risk of innovation failure and 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 overcome various risks associated with innovation failure. Failing to do so will reduce efficiency, market power, and ultimately liquidity creation.

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Tables

Table 1: M&A history in Indonesia

	(1) All	(2) Digital	(3) Non-digital	(4) t-test
Panel A: Acquisition length (months)				
Mean	6.2	3.3	7.4	
Median	3.0	3.0	4.0	
Panel B: Acquisition value				
Mean	$914 million	$52 million	$1,322 million	
Median	$48 million	$41 million	$57 million	
Panel C: Business performance				
Size	$1.6 billion	$1.9 billion	$1.6 billion	0.2936
Market share (%)	0.18	0.20	0.17	0.3827
Liquidity creation to assets (%)	10.5	8.51	11.6	0.2395
Lerner index	9.87	8.68	10.48	0.1848
Z-score	18.26	17.71	18.56	0.8821
Subordinated debt to assets (%)	0.53	0.53	0.53	0.9677
ROA (%)	-0.01	-0.26	0.12	0.7851
ROE (%)	-10.48	-15.73	-7.64	0.6777

Notes: This table documents the statistics of banks that experienced M&As. Panel A exhibits the average and median duration of the M&A transaction processes. Panel B shows the average and median of the transaction values. Panel C shows bank performance prior to M&As. Column 1 presents the average industry data. Column 2 displays the average data for digital banks. Column 3 exhibits the average data for non-digital banks. Column 4 displays the t-values of the mean-comparison tests with unequal variances.

Table 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). $LC = 1/2 \times illiquid\ assets - 1/2 \times liquid\ assets + 1/2 \times liquid\ liabilities - 1/2 \times illiquid\ liabilities - 1/2 \times equity + 1/2 \times illiquid\ guarantees - 1/2 \times liquid\ guarantees - 1/2\ liquidderivatives.$

Table 3: Variable descriptions

Variables	Definition	Unit
Digital	A dummy equal to 1 after a digital M&A, 0 otherwise	Dummy
LCI	Total liquidity creation using "cat fat" version of liquidity creation outlined by Berger and Bouwman (2009)	Per cent
LCIA	Asset-side liquidity creation	Per cent
LCIL	Liability-side liquidity creation	Per cent
LCIO	Off-balance sheet liquidity creation	Per cent
Lerner	Lerner index	Per cent
Costs	Operating costs to operating income	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
Size	Log assets	Logarithm
NPL	Non-performing loans 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
Derivatives	Derivatives to assets	Per cent

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

Table 4: Summary statistics

Variables	(1) Mean	(2) Median	(3) p10	(4) p90	(5) sd
LCI	11.2064	15.4973	-11.4441	27.9301	18.3460
LCIA	14.5913	19.5490	-8.6165	30.2642	16.3095
LCIL	-10.1791	-9.1612	-24.9028	6.8087	12.6347
LCIO	6.7943	4.4398	1.2442	15.5535	7.5196
Lerner	8.9793	7.7568	2.9292	16.0374	6.7876
Costs	97.8110	93.5900	69.1600	122.8500	42.6826
C&I loans	36.1068	36.9132	9.2545	58.1333	18.2229
Consumer loans	13.7685	8.3870	0.0423	39.2314	14.4392
Total loans	49.8753	52.5162	22.8389	66.6799	16.3531
Saving deposits	8.6464	6.2817	0.8884	20.0672	8.0522
Demand deposits	10.5245	5.6586	1.2065	29.7326	11.7492
Time deposits	36.6219	37.3411	6.5216	60.0702	19.8704
Total deposits	55.7928	62.1101	26.1639	73.3248	17.8994
Size	29.9714	29.9747	27.6875	31.9348	1.5269
NPL	4.2486	3.1850	0.1100	8.3000	4.8273
LLP	1.7562	1.1393	0.2282	3.3460	2.7866
Subdebt	0.3070	0.0000	0.0000	1.2979	0.9016
Zscore	19.4880	8.0598	1.1528	39.0920	44.0410
Derivatives	0.2146	0.0000	0.0000	0.0198	1.0332

Notes: This table provides the summary statistics for the variables used in the empirical analysis. Variable definitions are provided in Table 3.

Table 5: Balancedness test

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	*Digital*	*Size*	*NPL*	*Subdebt*	*Zscore*	*Derivatives*
Size	0.0805					
	(1.53)					
NPL	-0.0023					
	(-0.63)					
Subdebt	-0.0164					
	(-0.64)					
Zscore	-0.0003					
	(-1.33)					
Derivatives	-0.0071					
	(-0.73)					
Digital		0.4666	-1.2032	-0.2630	-9.2414	-0.0351
		(1.34)	(-0.68)	(-0.78)	(-1.02)	(-0.59)
Quarter FE	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES
Observations	708	708	708	708	708	708
R-squared	0.5364	0.9130	0.2672	0.4686	0.1715	0.8054

Notes: This table reports results on balancedness test outlined by Pei et al. (2019). Column 1 reports estimates of Equation (4). Columns 2-5 report tests for the balancedness in covariates using control variables as the outcome variables and bank digitalization as the main explanatory variable. Variable definitions are provided in Table 3. All regressions include bank and quarter fixed effects. 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 M&As and bank liquidity creation

	(1)	(2)	(3)	(4)
Dependent variable	*LCI*	*LCIA*	*LCIL*	*LCIO*
Digital	-18.8297**	-10.4807*	-8.1216**	-0.2275
	(-2.16)	(-1.81)	(-2.20)	(-0.07)
Size	0.1987	5.1187*	-2.5230	-2.3970*
	(0.04)	(1.82)	(-0.72)	(-1.79)
NPL	0.8618**	0.6600**	0.3035	-0.1017*
	(2.11)	(2.53)	(1.67)	(-2.05)
Subdebt	-0.6853	-0.0557	-1.0330**	0.4034
	(-1.00)	(-0.08)	(-2.24)	(1.10)
Zscore	-0.0213**	-0.0035	-0.0135***	-0.0043
	(-2.15)	(-0.44)	(-3.25)	(-1.09)
Derivatives	0.3302	-0.3983	0.5560**	0.1725***
	(0.66)	(-1.29)	(2.11)	(2.94)
Quarter FE	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES
Observations	708	708	708	708
R-squared	0.5576	0.7143	0.6299	0.7203

Notes: This table reports estimates of Equation (3) using total liquidity creation, asset-side liquidity creation, liability-side liquidity creation, and off-balance sheet liquidity creation. Variable definitions are provided in Table 3. All regressions include bank and quarter fixed effects. 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: Digital M&As, bank efficiency, and market power

	(1) All banks	(2) Small banks	(3) Other banks	(4) All banks	(5) Small banks	(6) Other banks
Dependent variable	*Costs*	*Costs*	*Costs*	*Lerner*	*Lerner*	*Lerner*
Digital	42.6558***	93.7287**	43.6076***	-3.3273*	-4.1079***	-0.1872
	(3.31)	(2.55)	(5.70)	(-1.84)	(-4.11)	(-0.11)
Controls	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES
Observations	708	183	525	708	183	525
R-squared	0.3823	0.5690	0.4214	0.6093	0.7548	0.6402

Notes: This table reports estimates of Equation (3) by splitting the sample into small and non-small banks. Columns 1-3 estimate the effect of digital M&As on operating costs. Columns 4-6 estimate the effect of digital M&As on the Lerner Index. The unreported control variables are log assets, non-performing loans to assets, subordinated debt to assets, z-score, and derivatives to assets. Variable definitions are provided in Table 3. All regressions include bank and quarter fixed effects. 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: Digital M&As and credit risk

Dependent variable	(1) NPL	(2) LLP	(3) LCI	(4) LCI
$Digital$	-1.0867	0.1907	-23.1393*	-23.7097**
	(-0.55)	(0.12)	(-1.83)	(-2.31)
$Digital \times NPL^{hi}$			13.8666	
			(0.93)	
NPL^{hi}			3.8249	
			(1.01)	
$Digital \times LLP^{hi}$				9.3522
				(0.68)
LLP^{hi}				13.1412
				(1.03)
Controls	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES
Observations	708	708	708	708
R-squared	0.2905	0.2845	0.5380	0.5488

Notes: This table reports the relationships between credit risk, digital M&As, and liquidity creation. Columns 1 and 2 report estimates of Equation (3) using non-performing loans to assets and loan loss provisions to assets as the outcome variables. Columns 3 and 4 examine the effects of the interaction between digital M&As and dummy variables representing high non-performing loans or loan loss provisions, respectively, on liquidity creation. The unreported control variables are log assets, subordinated debt to assets, z-score, and derivatives to assets. Variable definitions are provided in Table 3. All regressions include bank and quarter fixed effects. 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 9: The effect of digital M&As on bank loans and deposits

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Loans				Deposits	
Dependent variable	*C&I*	*Consumer*	*Total*	*Saving*	*Demand*	*Time*	*Total*
Digital	-11.3631**	-0.7606	-12.1237**	1.5827	-3.4521	-18.4155***	-20.2849***
	(-2.22)	(-0.31)	(-2.33)	(0.72)	(-1.16)	(-4.32)	(-4.67)
Controls	YES	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES
Observations	708	708	708	708	708	708	708
R-squared	0.7402	0.8860	0.6374	0.7476	0.7998	0.8434	0.6918

Notes: This table reports estimates of Equation (3) using C&I loans, consumer loans, total loans, saving deposits, demand deposits, time deposits, and total deposits as the outcome variables. The unreported control variables are log assets, non-performing loans to assets, subordinated debt to assets, z-score, and derivatives to assets. Variable definitions are provided in Table 3. All regressions include bank and quarter fixed effects. 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.

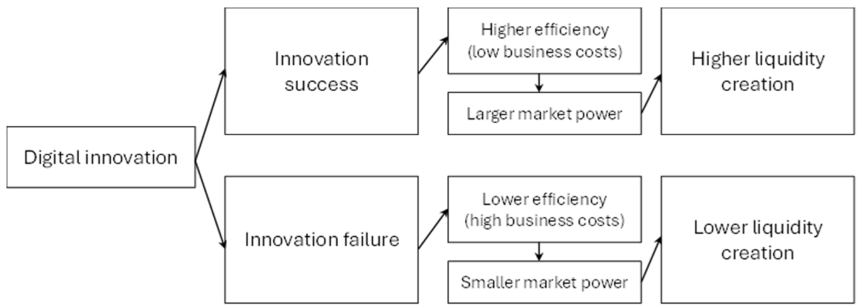
Table 10: Semi-parametric DID: Coefficient estimates and inferences

	(1)	(2)	(3)	(4)
Dependent variable	*LCI*	*LCIA*	*LCIL*	*LCIO*
Digital	-14.5589***	-5.1730**	-6.8775***	-2.5084***
	(-4.23)	(-2.00)	(-2.92)	(-3.01)
Controls	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES
Observations	396	396	396	396

Notes: This table reports estimates of the average treatment effect (ATE) of digital M&As on the outcome variables using semi-parametric DID estimation outlined by Abadie (2005). Observations with propensity scores greater than 0.99 and less than 0.01 are excluded from the sample to create a more balanced comparison. The unreported control variables are log assets, non-performing loans to assets, subordinated debt to assets, z-score, and derivatives to assets. Variable definitions are provided in Table 3. All regressions include bank and quarter fixed effects. 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.

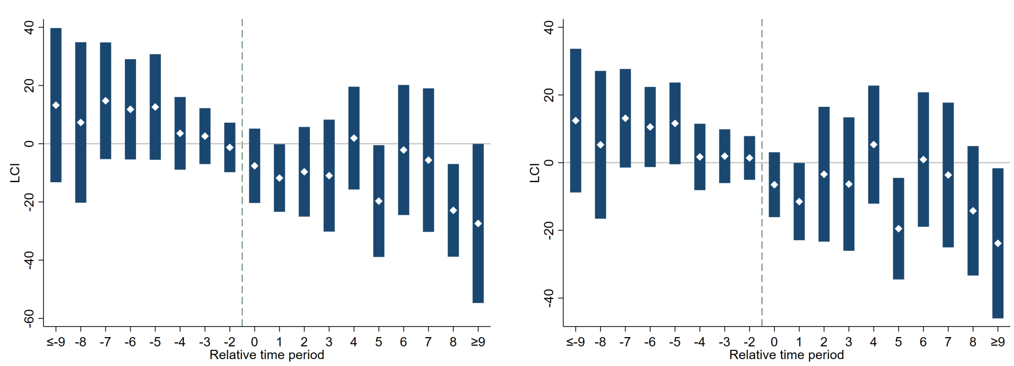
Figures

Figure 1: Conceptual framework



Notes: The figure visualizes the consequences of innovation within a firm following the innovation taxonomy outlined by Baxter et al. (2023). Quick and smooth integration of new technology improves efficiency, strengthens market power, and increases liquidity creation. In contrast, the failure of incorporating new technology can undermine business efficiency and market power, eventually reducing liquidity creation.

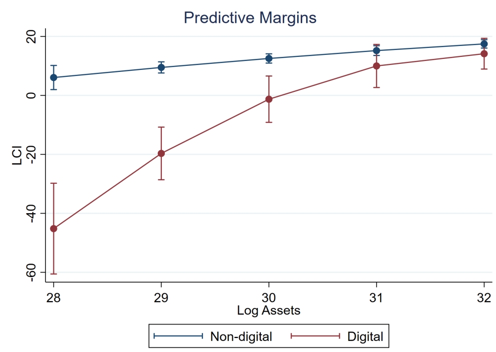
Figure 2: Event study: Digital transformation and bank liquidity creation



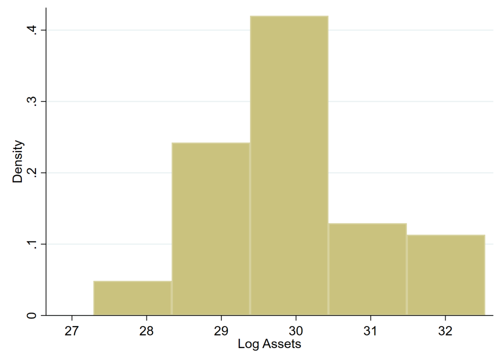
(a) TWFE-DID (b) Stacked DID

Notes: The graph illustrates the estimated dynamic coefficients and 90% confidence intervals for the effects of digital M&As on bank liquidity creation. Panel (a) shows estimates of the TWFE-DID estimator, while panel (b) exhibits the results of stacked DID estimator. The dynamic coefficients show the quarterly average difference in the outcome variable between banks subject to digital M&As (the treatment group) and banks that are not (the control group).

Figure 3: Interaction between bank size and liquidity creation



(a) Polynomial spline



(b) Asset distribution of digital banks

Notes: Panel (a) illustrates non-parametric estimates using a polynomial spline of order 2. The 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 $(x_{i,t}, z_{i,t}, x_{i,t}z_{i,t}, x^2_{i,t}, z^2_{i,t}, x^2_{i,t}z^2_{i,t})$. The 95% confidence intervals denoted by the vertical lines around each coefficient. Panel (b) illustrates the histogram of log assets within digital bank.

Online Appendix

A Additional regression results

Table A.1: Cox (1972) proportional hazard model

	(1)	(2)	(3)	(4)
Dependent variable	*Digital*	*Digital*	*Digital*	*Digital*
$LCIA$	-0.0060			
	(-0.49)			
$LCIL$		-0.0188		
		(-0.88)		
$LCIO$			-0.0755	
			(-1.06)	
LCI				-0.0137
				(-1.49)
Controls	YES	YES	YES	YES
Observations	708	708	708	708

Notes: This table reports Cox (1972) proportional hazard (Cox PH) model to verify that our main specification is not threatened by simultaneity bias. I use a Cox model that does not impose a shape on the hazard function, i.e., $h\left(t|x_i\right) = h_0(t)\exp(x_i\beta_x)$, 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.

Table A.2: Other balance sheet components

	(1)	(2)	(3)	(4)
Dependent variable	*Cash*	*Securities*	*Borrowings*	*Equity*
Digital	-0.0268	7.5785	0.0969	16.5526***
	(-0.01)	(1.15)	(0.16)	(3.23)
Controls	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES
Observations	708	708	708	708
R-squared	0.5445	0.5528	0.1877	0.7658

Notes: This table reports estimates of Equation (3) using cash equivalents, total securities, total long-term borrowings, and total equity as the outcome variables. The unreported control variables are log assets, non-performing loans to assets, subordinated debt to assets, z-score, and derivatives to assets. Variable definitions are provided in Table 3. All regressions include bank and quarter fixed effects. 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 A.3: Further sensitivity analysis

	(1)	(2)	(3)	(4)
Dependent variable	*LCI*	*LCI*	*LCI*	*LCI*
Digital	-19.4084**	-30.1400*	-16.2938*	-21.8412*
	(-2.14)	(-1.87)	(-1.79)	(-1.93)
$Digital \times COVID$		12.4786		
		(0.98)		
$Digital \times GDP$			-0.7885	
			(-0.72)	
$Digital \times Rate$				5.8454
				(0.55)
Controls	NO	YES	YES	YES
Quarter FE	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES
Observations	708	708	708	708
R-squared	0.5175	0.5591	0.5585	0.5602

Notes: This table reports estimates of Equation (3) augmented with COVID-19 pandemic dummy, GDP growth, and central bank policy dummy. The unreported control variables are log assets, non-performing loans to assets, subordinated debt to assets, z-score, and derivatives to assets. Variable definitions are provided in Table 3. All regressions include bank and quarter fixed effects. 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 A.4: Oster (2019) Coefficient Stability

Panel A: No controls to all controls								
	QE controls		All controls		R^2_{max}		Bounding values	
Specification	$\dot{\beta}$	$\dot{R}^2$	$\tilde{\beta}$	$\tilde{R}^2$	$\Pi = 1.2$	$\Pi = 1.5$	$\beta^*_{\Pi=1.2}$	$\beta^*_{\Pi=1.5}$
LCI	-19.0808	0.083	-18.8297	0.558	0.670	0.837	-18.7707	-18.6822
$LCIA$	-12.2782	0.043	-10.4807	0.714	0.857	1.000	-10.0981	-9.7145
$LCIL$	-5.2688	0.013	-8.1216	0.630	0.756	0.945	-8.7042	-9.5781
$LCIO$	-1.5339	0.003	-0.2275	0.720	0.864	1.000	0.0349	0.2827

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, I follow Oster (2019) by using $R^2 = \min(1, \Pi \cdot \tilde{R}^2)$ with $\Pi = 1.2$ as my benchmark and my more conservative value of $\Pi = 1.5$.

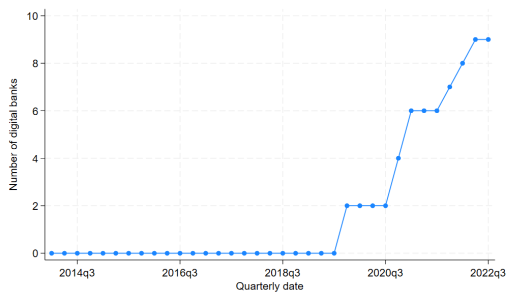
Table A.5: Block bootstrap standard error

Dependent variable	(1) *LCI*	(2) *LCIA*	(3) *LCIL*	(4) *LCIO*
Digital	-18.8297**	-10.4807*	-8.1216**	-0.2275
	(-2.36)	(-1.84)	(-2.12)	(-0.08)
Controls	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES
Observations	708	708	708	708
R-squared	0.2509	0.3684	0.1386	0.1183

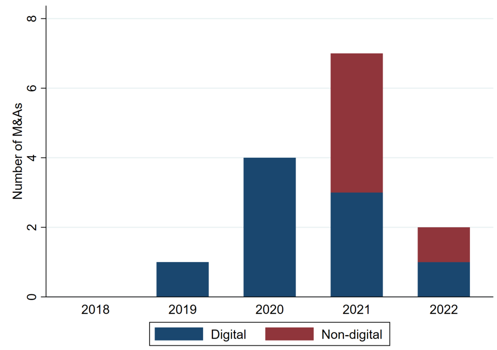
Notes: This table reports estimates of Equation (3) using total liquidity creation, asset-side liquidity creation, liability-side liquidity creation, and off-balance sheet liquidity creation. The unreported control variables are log assets, non-performing loans to assets, subordinated debt to assets, z-score, and derivatives to assets. Variable definitions are provided in Table 3. All regressions include bank and quarter fixed effects. The standard errors are block bootstrapped, where the block is defined based on treatment status. The corresponding t-statistics are reported in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

B Additional figures

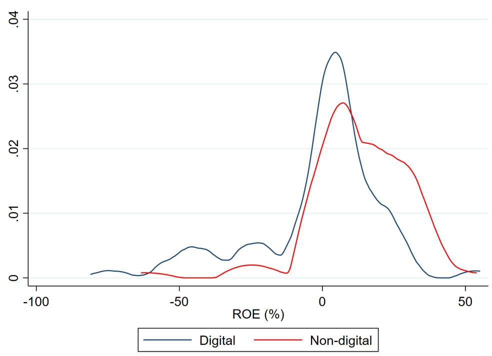
Figure B.1: The evolution of digital banks in Indonesia



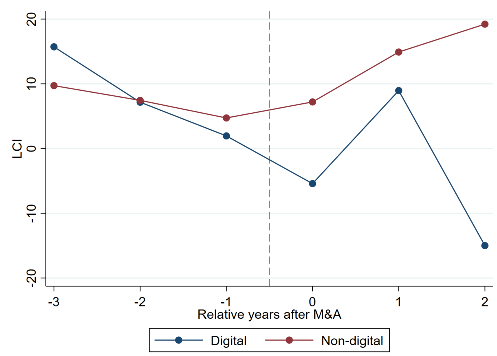
(a) Number of digital banks



(b) Total digital M&As vs non-digital M&As



(c) Performance prior M&As



(d) The trends of liquidity creation

Notes: The figures visualize various data associated with the evolution of digital banks in Indonesia. Panel (a) illustrates the number of established digital banks between 2014 and 2022, which increased from 0 in 2018 to 9 in 2022. Panel (b) shows total digital and non-digital M&As after the issuance of the OJK regulation on digital services in the banking sector in 2018. The graph shows that non-digital M&As still occurred even after the issuance of the regulation in 2018. Panel (c) compares the performance of digital banks and non-digital banks prior M&As, represented by return on equity (ROE) and exhibits no significant difference between both groups. This confirms that bank performance is not the primary objective of digital M&As. Panel (d) exhibits the trends of liquidity creation in digital banks and non-digital banks. The graph shows that liquidity creation is lower after digital M&As compared to non-digital M&As.