The Impact of Instant Payment System Adoption on Bank Liquidity, Deposit Structure, and Risk-Taking Behavior

Yuqi Shi

February 25, 2025

1 Introduction

This document presents an empirical research exercise that applies causal inference techniques to analyze the impact of an instant payment system adoption on bank liquidity, deposit structures, and risk-taking behavior. The study uses a Difference-in-Differences (DiD) framework and an event study approach to quantify the effects of policy adoption on financial institutions.

The analysis leverages panel data methods with fixed effects, clustered standard errors, and control variables to account for macroeconomic factors and bank-level heterogeneity. The key research questions addressed in this section include:

1. **Bank Liquidity Ratios** – Does adopting an instant payment system increase liquidity holdings?
2. **Deposit Structure** – How does the adoption affect checking, savings, and time deposit ratios?
3. **Risk-Taking Behavior** – Do banks adjust their lending strategies by shifting between low-risk and high-risk loans?

This study demonstrates my ability to work with large financial datasets, apply econometric techniques, and interpret empirical results in a structured research setting. The findings contribute to the understanding of how technological advancements in payment systems impact financial institutions' behavior.

2 Identification Exercise

2.1 Impact on Bank Liquidity Ratios

Firstly, the adoption of the instant payment system is expected to increase the liquidity ratio, as banks may hold more liquid assets to accommodate real-time transactions. The reduction in settlement delays and increased transaction speed encourage banks to maintain higher cash reserves and government bond holdings, ensuring smooth fund transfers.

$$\text{LiquidityRatio}_{it} = \frac{\text{Cash}_{it} + \text{GovBond}_{it}}{\text{Assets}_{it}} \tag{1}$$

Given the equation of the Liquidity Ratio, to estimate the impact of the instant payment system adoption on bank liquidity ratios, I employed a Difference-in-Differences (DiD) approach. Given the staggered adoption of the introduction of the instant payment system across banks, both a simple DiD specification and an event study framework were used to capture dynamic effects over time. The baseline regression follows a standard DiD specification:

$$\text{LiquidityRatio}_{it} = \beta_1 \cdot \text{Post}_{it} + \alpha_i + \theta_t + \epsilon_{it} \tag{2}$$

where $\text{LiquidityRatio}_{it}$ represents the liquidity ratio of bank i at time t. The variable Post_{it} is an indicator equal to one if bank i has adopted the instant payment system by time t and zero otherwise. The coefficient β_1 captures the average treatment effect of the adoption of the payment system on liquidity. α_i and θ_t denote bank and time fixed effects, respectively. They are included to control for time-invariant bank characteristics and macroeconomic shock. And the error term ϵ_{it} accounts for unobserved bank-specific shocks.

	(1)
VARIABLES	Impact on Liquidity Ratio
post	0.0166**
	(0.00802)
t-stat:	2.065
p-val:	0.0392
Constant	0.0341***
	(0.00145)
t-stat:	23.53
p-val:	0
Observations	47,932
Number of banks	983
R-squared	0.006

Robust se pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 1: Impact on Bank Liquidity Ratio

The staggered Difference-in-Differences (DiD) regression suggests that banks adopting the instant payment system experienced a 1.66 percentage point increase in their liquidity ratio, statistically significant at 5 percent level. The relatively low R^2 value indicates that while the policy had a measurable effect, other bank-level and macroeconomic factors likely contribute to liquidity trends. The p-value of 0.0392 indicates moderate confidence in the effect. Thus, it gives us a significant overall effect of the introduction of the instant payment system.

To examine the dynamic effects of policy adoption and validate the parallel trends assumption, we estimate an event study regression:

$$\text{LiquidityRatio}_{it} = \sum_{\tau \neq -1} \beta_\tau \cdot \text{EventTime}_{it}^{\tau} + \gamma X_{it} + \alpha_i + \theta_t + \epsilon_{it} \tag{3}$$

where $\text{EventTime}_{it}^{\tau}$ is a set of dummies indicating months relative to policy adoption for bank i. The coefficients β_τ capture the treatment effect at different points before and after adoption. Standard errors are clustered at the bank level to account for within-bank correlation. Control variables such as `log_assets`, `capital_ratio`, and `loan_deposit_ratio` account for differences in bank size, financial stability, and liquidity risk. I also include `cash`, `govbond`, and `loan_total` to control for variations in asset holdings and lending activity. These controls ensure that observed effects are due to policy adoption rather than bank-specific factors.

VARIABLES	(1) Baseline	(2) Baseline With Controls
event_neg10	-0.00776	-0.00307
	(0.00655)	(0.00645)
event_neg5	0.000164	0.00578
	(0.0101)	(0.0106)
event_neg2	-0.00300	-0.000445
	(0.00811)	(0.00839)
event_0	-0.00274	-0.00293
	(0.00589)	(0.00599)
event_2	0.00548	0.00323
	(0.00559)	(0.00544)
event_5	0.0105	0.0107
	(0.00740)	(0.00705)
event_10	0.00995	0.00514
	(0.00788)	(0.00755)
event_20	0.00763	-0.00333
	(0.00944)	(0.00737)
log_assets		-0.0174*
		(0.00969)
capital_ratio		0.0819**
		(0.0377)
loan_deposit_ratio		3.78e-09**
		(1.63e-09)
cash		-3.48e-07
		(6.93e-07)
govbond		1.44e-06**
		(5.61e-07)
loan_total		-1.67e-07**
		(7.18e-08)
Constant	0.0341***	0.103*
	(0.00145)	(0.0546)
Observations	47,932	37,863
R-squared	0.004	0.038
Number of bank_id	983	802

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 2: Baseline and Control Result for Liquidity Ratio

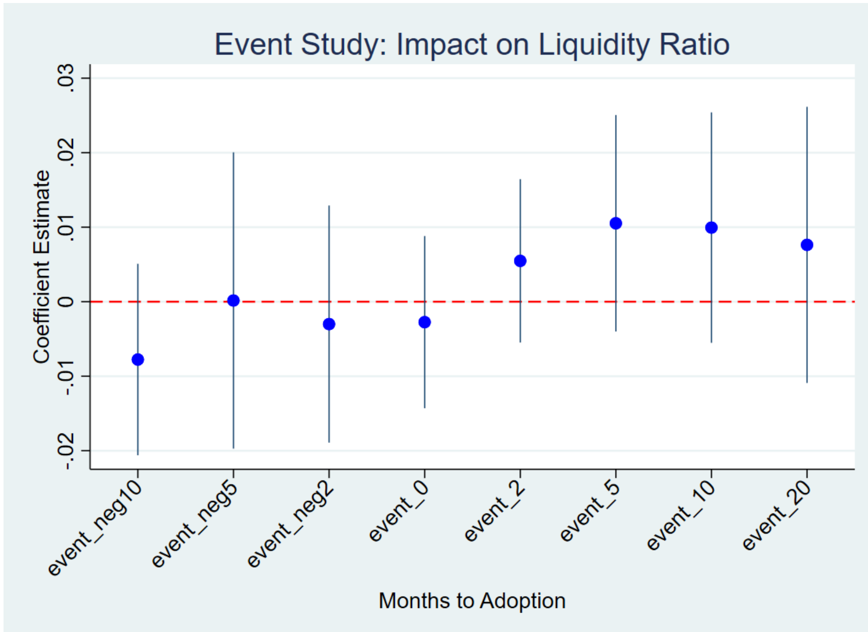
In the baseline specification, the coefficients for post-adoption event time indicators are positive, suggesting that the adoption of the instant payment system is associated with an increase in the liquidity ratio. However, the estimated coefficients are not statistically significant, indicating that the effect may be small or that there is substantial variation between banks. The pretreatment coefficients are close to zero, supporting the validity of the parallel trends assumption.

When control variables are included in Column (2), the magnitude of the estimated post-adoption effects remains similar, though the coefficient on event_20 becomes slightly negative. The inclusion of control variables increases the explanatory power of the model, as reflected in the higher R^2 value (0.038 compared to 0.004 in the baseline model). Among the control variables, the capital ratio is positively and significantly associated with the liquidity ratio, indicating that banks with higher capital reserves tend to maintain a higher proportion of liquid assets. Similarly, the loan-to-deposit ratio shows statistical significance, though its coefficient is relatively small in magnitude.

Thus, these results suggest that while the introduction of the instant payment system may have contributed to an increase in liquidity ratios, the effect is not strongly significant. The inclusion of control variables does not substantially alter the main conclusions.

The event study plot confirms that pre-treatment coefficients (event_neg10, event_neg5, event_neg2) are close to zero, supporting the validity of the parallel trends assumption. Post-adoption coefficients

Figure 3: Event Study: Impact on Liquidity Ratio



(event_2, event_5, event_10) indicate a positive trend in liquidity ratios after the policy was implemented, though confidence intervals suggest some degree of uncertainty.

In conclusiopn, the findings suggest that the introduction of the instant payment system had a small but positive effect on bank liquidity ratios.

2.2 Changes in Bank Deposit Structure

The introduction of instant payments is expected to increase checking deposit ratios, as individuals and businesses shift funds toward highly liquid accounts to facilitate frequent transactions. In contrast, the effect on saving deposits is less certain, but a potential decline is expected as consumers prioritize liquidity. With instant payments reducing the need for precautionary savings, individuals may withdraw from savings accounts to fund daily transactions. I think time deposits may experience a same decline or remain stable, as the need for locked-in deposits diminishes. The improved efficiency of instant transactions reduces liquidity constraints, making short-term accessible funds more attractive than long-term deposits.

To start to investigate potential shifts in demandable deposit ratios, three ratios could be defined by the following equations:

$$\text{Checking Deposit Ratio} = \frac{\text{Checking Deposits}}{\text{Total Deposits}} \tag{4}$$

$$\text{Saving Deposit Ratio} = \frac{\text{Saving Deposits}}{\text{Total Deposits}} \tag{5}$$

$$\text{Time Deposit Ratio} = \frac{\text{Time Deposits}}{\text{Total Deposits}} \tag{6}$$

Given these equations of the deposit ratios, I still showed a standard DiD specification first and staggered DiD next. The regression equation used to estimate the impact of instant payment adoption on bank deposit structures is given by:

$$\log D_{it} = \beta_1 \cdot \text{Post}_{it} + \alpha_i + \theta_t + \varepsilon_{it} \tag{7}$$

The dependent variable $\log D_{imt}$ represents the log-transformed deposit ratios (*checking, saving, or time deposits*) for bank i at time t. The key explanatory variable, Post_{it}, is an indicator that equals 1 if the bank has adopted the instant payment system and 0 otherwise. Bank fixed effects (α_i) and time fixed effects (θ_t) are included to control for time-invariant bank characteristics and macroeconomic shocks. The coefficient β_1 captures the effect of instant payment adoption on deposit composition. Standard errors are clustered at the bank level. Standard errors are clustered at the bank level to account for serial correlation and heteroskedasticity within banks over time. Since each bank is observed across multiple time periods, observations within the same bank are likely correlated, violating the assumption of independent errors.

Table 1: Effect of Instant Payments on Bank Deposit Ratios

	Checking Deposits	**Saving Deposits**	**Time Deposits**
Post	0.180	-0.194**	0.015
	(0.137)	(0.041)	(0.084)
Bank FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Controls	No	No	No
Observations	47,932	47,932	47,932
Within R^2	0.0379	0.0682	0.007

Notes: This table reports estimates of the impact of instant payments on different types of deposit ratios. Standard errors (in parentheses) are clustered at the bank level. Bank and time fixed effects are included. *, **, and *** correspond to 10-, 5-, and 1% significance levels, respectively.

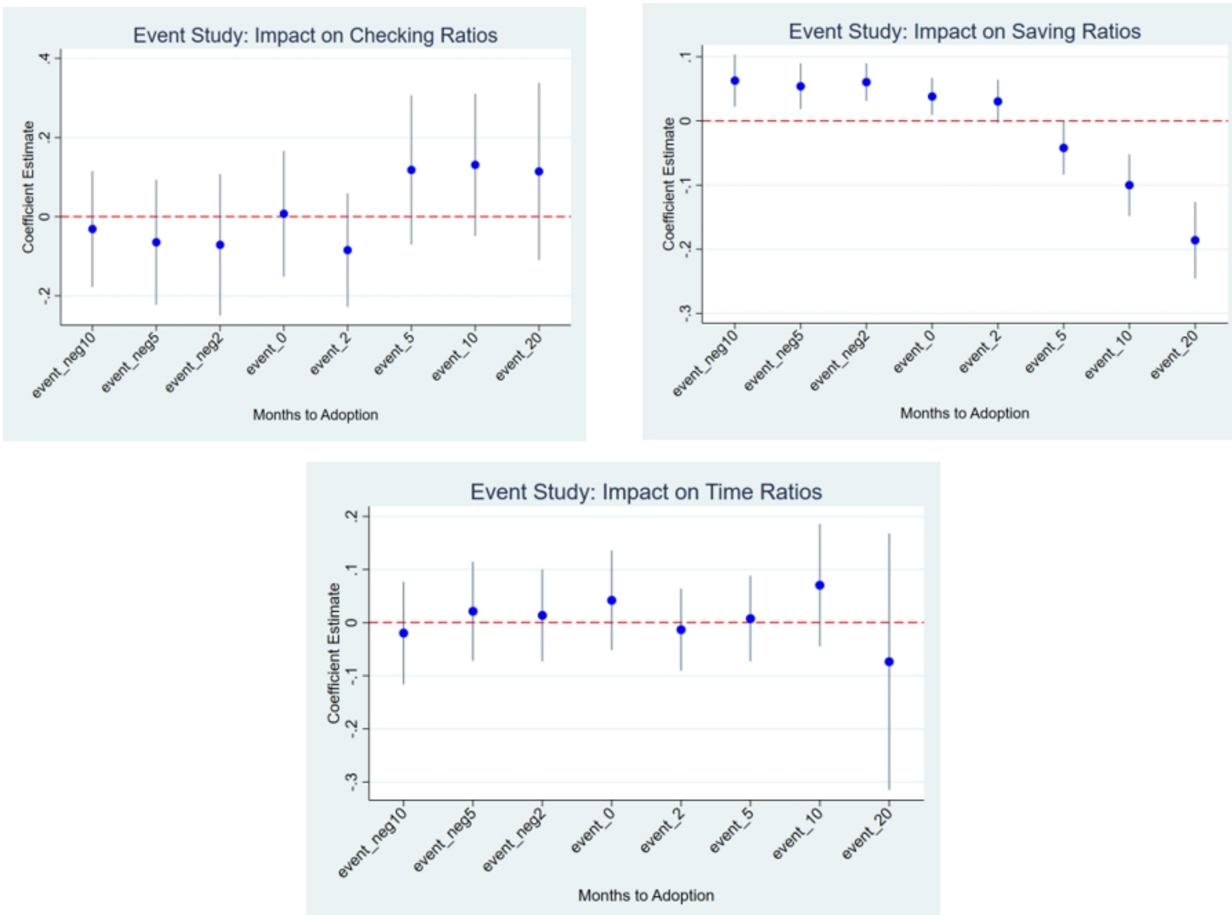
The table presents the estimated impact of instant payment adoption on different types of bank deposits, focusing on checking, saving, and time deposit ratios. The coefficient on the post-treatment indicator for checking deposits is positive (0.180) but not statistically significant, suggesting a potential increase in checking deposits following adoption, though the effect remains uncertain.

For saving deposits, the estimate is negative and statistically significant at the 5% level (-0.194**), indicating a reduction in saving deposit ratios after adoption. However, the validity of this estimate is questionable as the event study results suggest that the parallel trends assumption does not hold for saving deposits, making the difference-in-differences (DiD) approach unsuitable for this outcome. The coefficient for time deposits is small (0.015) and statistically insignificant, implying no strong evidence of an effect.

While some estimates lack statistical significance, it is important to assess their economic relevance by considering direction and magnitude. The positive but insignificant coefficient on checking deposits aligns with the expectation that instant payments could increase demand for liquid accounts. The negative estimate for saving deposits, although significant, should not be overinterpreted due to violations of the identification assumption. The results remain robust to the inclusion of fixed effects at the bank and time levels, with standard errors clustered at the bank level to account for within-bank correlation. Future analysis may explore alternative approaches to validate these findings.

The event study analysis for checking and time deposit ratios suggests that the parallel trends assumption holds, as the pretreatment coefficients (event_neg10, event_neg5, event_neg2) are statistically indistinguishable from zero, indicating no significant pretrend differences. This validates the use of the difference-in-differences (DiD) approach for these two outcomes.

Figure 4: Event Study: Impact on the Deposit Ratios



However, for saving deposit ratios, the pre-treatment coefficients show a clear downward trend, violating the parallel trends assumption. This suggests that treated and control banks had divergent trends in saving deposits even before the adoption of instant payments, making the DiD estimates unreliable for this variable.

To examine the dynamic effects of the adoption of the system and validate the parallel trends assumption for deposit ratios, we estimate an event study regression:

$$\log D_{it} = \sum_{\tau \neq -1} \beta_\tau \cdot \text{EventTime}_{it}^{\tau} + \gamma X_{it} + \alpha_i + \theta_t + \epsilon_{it} \tag{8}$$

The equation specifies a Staggered DiD to analyze the impact of instant payment adoption on deposit ratios. The dependent variable, $\log D_{it}$, represents the logarithm of the deposit ratio for bank i at time t. The summation term $\sum_{\tau \neq -1} \beta_\tau \cdot EventTime_{it}^{\tau}$ captures the time-varying treatment effects, where each coefficient β_τ estimates the relative change in deposit ratios at different event time periods τ relative to the pre-adoption baseline period $\tau = -1$. The vector γX_{it} represents control variables, while α_i and θ_t denote bank fixed effects and time fixed effects. The error term ϵ_{it} accounts for unobserved heterogeneity.

As we could see above, the inclusion of bank-level controls (log assets, capital ratio, loan-deposit ratio, cash, government bonds, and total loans) in Columns 2 and 4 improves the explanatory power, as indicated by the higher R^2. The coefficient for event_2 in Column 2 becomes statistically significant ($p < 0.1$), suggesting a potential small negative short-term effect of adoption on the checking deposit ratio

Figure 5: Baseline and Controls Results for the Deposit Ratios

VARIABLES	(1) Log Checking Ratio Baseline	(2) Log Checking Ratio Baseline With Controls	(3) Log Time Ratio Baseline	(4) Log Time Ratio Baseline With Controls
event_neg10	-0.0312	-0.0159	-0.0197	-0.0301
	(0.0746)	(0.0560)	(0.0492)	(0.0477)
event_neg5	-0.0648	-0.0658	0.0214	-0.00642
	(0.0806)	(0.0599)	(0.0475)	(0.0500)
event_neg2	-0.0712	-0.0653	0.0136	-0.0119
	(0.0911)	(0.0725)	(0.0441)	(0.0452)
event_0	0.00736	0.00705	0.0420	0.0146
	(0.0810)	(0.0610)	(0.0477)	(0.0508)
event_2	-0.0846	-0.0777*	-0.0133	-0.0268
	(0.0732)	(0.0435)	(0.0394)	(0.0459)
event_5	0.118	0.0140	0.00760	-0.0135
	(0.0962)	(0.0719)	(0.0412)	(0.0423)
event_10	0.131	0.0155	0.0705	0.0470
	(0.0916)	(0.0751)	(0.0588)	(0.0563)
event_20	0.114	0.00860	-0.0735	-0.106
	(0.114)	(0.0891)	(0.123)	(0.126)
log_assets		0.0242		-0.0209
		(0.0521)		(0.0756)
capital_ratio		0.130		0.0202
		(0.335)		(0.423)
loan_deposit_ratio		4.04e-07***		-2.83e-06***
		(6.70e-08)		(2.26e-08)
cash		3.27e-06		-7.02e-06
		(4.36e-06)		(6.43e-06)
govbond		-1.16e-06		4.72e-06
		(1.70e-06)		(3.48e-06)
loan_total		-9.14e-09		3.26e-07
		(5.75e-07)		(3.69e-07)
Constant	-3.216***	-2.408***	-1.806***	-0.395
	(0.0207)	(0.293)	(0.0234)	(0.395)
Observations	47,932	37,863	47,932	37,863
R-squared	0.036	0.080	0.007	0.059
Number of banks	983	802	983	802

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

which is a bit surprising. Additionally, the loan-deposit ratio is highly significant in both specifications, but its actual economic effect is very small which means that even large changes in the loan-deposit ratio will have negligible practical impact on checking and time deposit ratios.

Overall, the results suggest that instant payment adoption may influence the composition of deposits, with a possible short-term decline in checking deposit ratios around event_2. However, no strong long-term effects are observed for time deposit ratios. The inclusion of controls does not drastically change the interpretation of event-time coefficients, indicating robustness.

2.3 Assess Risk-Taking Behavior

In this part, we could expect that the introduction of an instant payment system changes banks' liquidity needs, which may influence their lending behavior. If the system improves liquidity management, banks may feel more comfortable extending riskier loans. Conversely, if the system increases liquidity pressure, banks may reduce risk-taking.

To assess the risk taking behavior, I divide the loan risk scales into two groups (low-risk group and high-risk group) and separately ran DiD on each of them. The two groups could be defined:

$$\text{Low Risk Ratio} = \frac{\text{loan AA} + \text{loan A} + \text{loan B} + \text{loan C}}{\text{Total Loan}} \tag{9}$$

$$\text{High Risk Ratio} = \frac{\text{loan D} + \text{loan E} + \text{loan F} + \text{loan G} + \text{loan H}}{\text{Total Loan}} \tag{10}$$

The standard DiD regression equation is thus defined as:

$$\log R_{it} = \beta_1 \cdot \text{Post}_{it} + \alpha_i + \theta_t + \varepsilon_{it} \tag{11}$$

The dependent variable $\log R_{imt}$ represents either low-risk loan ratio or high-risk loan ratio for bank i at time t. The key explanatory variable, Post_{it}, is an indicator that equals 1 if the bank has adopted the instant payment system and 0 otherwise. Bank fixed effects (α_i) and time fixed effects (θ_t) are included to control for time-invariant bank characteristics and macroeconomic shocks, same as above.

Table 2: Effect of Instant Payments on Risk Ratios

	Low Risk Ratio	**High Risk Ratio**
Post	0.0096	-0.0119
	(0.011)	(0.109)
Bank FE	Yes	Yes
Time FE	Yes	Yes
Controls	No	No
Observations	46,691	46,691
Within R^2	0.0035	0.0363

Notes: This table reports estimates of the impact of instant payments on share of risky loan ratio. Standard errors (in parentheses) are clustered at the bank level. Bank and time fixed effects are included. *, **, and *** correspond to 10-, 5-, and 1% significance levels, respectively.

As table 2 shown above, we could see that the coefficient on Post for the low-risk ratio is 0.0096, suggesting a slight increase in the share of low-risk loans after the adoption of the instant payment system. However, the estimate is not statistically significant. The coefficient on Post for the high-risk ratio is -0.0119, indicating a small decrease in the share of high-risk loans, but the estimate is also not statistically significant. The results indicate no strong evidence that banks significantly altered their risk-taking behavior in response to the adoption of the instant payment system. Thus, a staggered DiD approach is introduced to capture the effect.

Figure 6: Event Study: Impact on Low Risk Loan Ratio

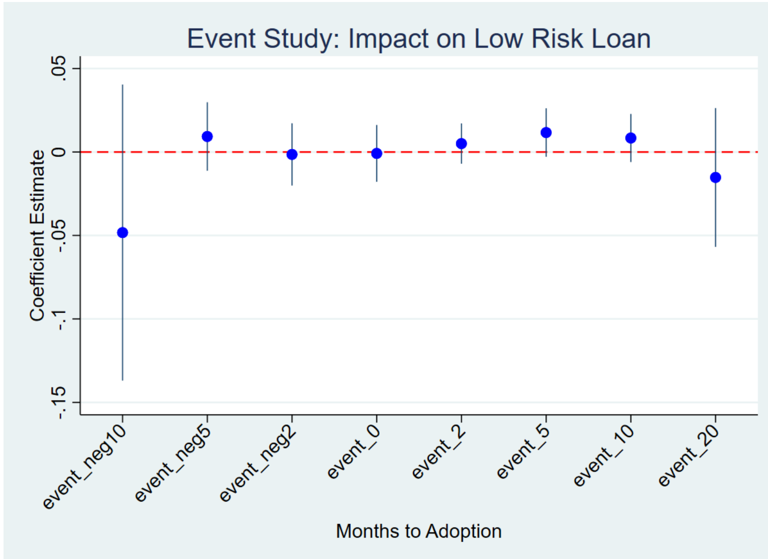
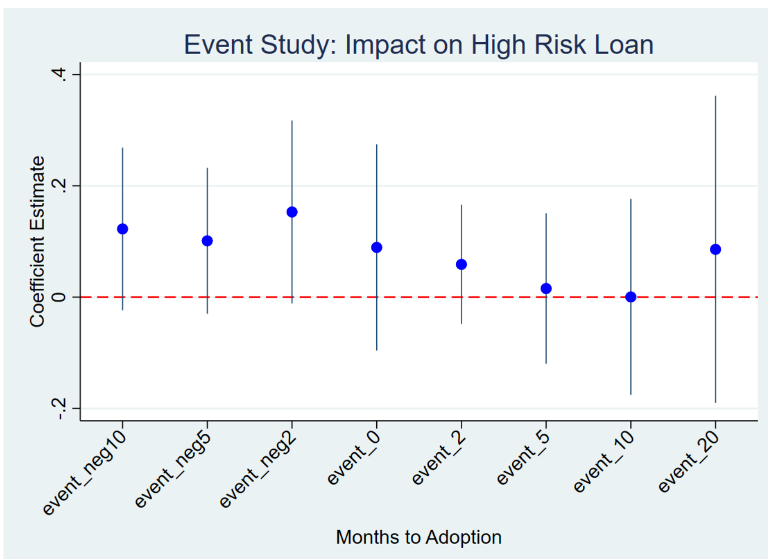


Figure 7: Event Study: Impact on High Risk Loan Ratio



The event study plot for the low-risk loan ratio suggests that the parallel trends assumption is kind of satisfied before the adoption of the instant payment system. The coefficient estimates for pre-adoption periods (event times ¡ 0) remain close to zero,treated and control banks followed similar trends before treatment. And the coefficients mainly concentrated near 0, especially closer to the date of adoption. For the high-risk loan ratio, the parallel trends assumption is less clear, as the pre-adoption coefficients exhibit some variation around zero. We could see that there are potential differences in pre-trends between treated and control banks.

Thus, the staggered DiD regression that can examine the dynamic effects of the payment system adoption is:

$$\log R_{it} = \sum_{\tau \neq -1} \beta_\tau \cdot \text{EventTime}_{it}^{\tau} + \gamma X_{it} + \alpha_i + \theta_t + \epsilon_{it} \tag{12}$$

Except for the dependent variable changing to Risk loan ratio, the equation holds the same with the equations mentioned earlier. The dependent variable, $\log R_{it}$, represents the logarithm of the risk loan ratios for bank i at time t. Other terms maintain the same and control variables remain as well.

Figure 8: Baseline and Controls Results for the Risk Ratios

VARIABLES	(1) Log Low Risk Ratio Baseline	(2) Log Low Risk Ratio Baseline With Controls	(3) Log High Risk Ratio Baseline	(4) Log High Risk Ratio Baseline With Controls
event_neg10	-0.0483	-0.0472	0.123	0.114
	(0.0452)	(0.0466)	(0.0745)	(0.0775)
event_neg5	0.00930	-0.00736	0.101	0.124*
	(0.0105)	(0.00687)	(0.0668)	(0.0679)
event_neg2	-0.00146	-0.0132*	0.153*	0.171**
	(0.00950)	(0.00787)	(0.0837)	(0.0862)
event_0	-0.000844	-0.0109	0.0893	0.103
	(0.00867)	(0.00720)	(0.0944)	(0.101)
event_2	0.00504	-0.000680	0.0588	0.0817
	(0.00615)	(0.00563)	(0.0546)	(0.0575)
event_5	0.0117	0.00781	0.0155	0.0397
	(0.00741)	(0.00765)	(0.0689)	(0.0722)
event_10	0.00839	0.00289	0.000301	0.0208
	(0.00733)	(0.00677)	(0.0897)	(0.0897)
event_20	-0.0152	-0.0183	0.0858	0.0672
	(0.0212)	(0.0210)	(0.141)	(0.147)
log_assets		0.0353**		-0.188*
		(0.0168)		(0.0981)
capital_ratio		-0.00139		-0.474
		(0.0682)		(0.438)
loan_deposit_ratio		-2.23e-08***		5.45e-07***
		(3.68e-09)		(2.03e-08)
cash		8.68e-07		-9.37e-06
		(6.45e-07)		(7.68e-06)
govbond		-2.90e-07**		3.72e-06*
		(1.38e-07)		(2.10e-06)
loan_total		-1.14e-08		1.72e-07
		(6.30e-08)		(5.65e-07)
Constant	-0.115***	-0.294***	-2.917***	-1.587***
	(0.00794)	(0.0968)	(0.0232)	(0.563)
Observations	46,691	37,193	46,691	37,193
R-squared	0.004	0.014	0.036	0.066
Number of banks	967	789	967	789

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

To interpret the results of the table, for low-risk loans, the coefficients on event_time dummies remain small and statistically insignificant, which means no substantial change in the share of low-risk loans following adoption. The coefficient on event_neg2 in column (2) is significant at the 10% level, but its magnitude is small, indicating a slight decline in low-risk loans just before adoption date. Also, the coefficient on log_assets is positive and significant, showing that larger banks tend to have a higher share of low-risk loans. The negative and significant coefficient on loan_deposit_ratio suggests that banks with higher loan-to-deposit ratios tend to allocate fewer resources to low-risk loans.

For high-risk loans, the results shows a different pattern. The coefficients for event_neg2, event_5, and event_10 are positive and significant, suggesting that banks may have increased their share of high-risk loans in the period surrounding adoption. The effect is more clear in the specification with controls (column 4), where event_10 and event_20 remain positive, though not statistically significant. This indicates that banks might have taken on slightly more high-risk loans following adoption, but the effect is not strongly persistent over time. Additionally, log_assets is negatively associated with high-risk loans, meaning larger banks allocate a smaller portion of their portfolios to riskier loans. Similar to low-risk loans, the loan_deposit_ratio coefficient is significant, though in the opposite direction, implying that banks with more aggressive lending strategies tend to hold a larger share of risky loans.

In conclusion, the findings suggest that instant payment adoption did not significantly impact low-risk lending but may have led to a temporary increase in high-risk loans. However, the lack of strong and persistent significance in post-adoption periods suggests that this shift is not robust across time.

2.4 Appendix

Figure 9: Summary Statistics for Treatment and Control Group

Summary Statistics: Treatment Group

Variable	Obs	Mean	Std.Dev.	Min	Max
asset	1415	143000	423000	12.05	2240000
cash	1415	2034.522	6830.802	0	51352.79
govbond	1415	8490.529	22788.42	0	171000
deposit	1415	55477.21	165000	0	892000
deposit_ch~g	1415	7003.099	25488.46	0	172000
deposit_sa~g	1415	11739.94	41506.81	0	226000
deposit_time	1415	34321.47	98222.91	0	569000
loan_total	1415	56111.9	169000	0	898000
corecapital	1415	11418.6	33077.61	1.117	160000

Summary Statistics: Control Group

Variable	Obs	Mean	Std.Dev.	Min	Max
asset	46517	4593.124	63007.89	0	1980000
cash	46517	56.788	1068.854	0	47288.5
govbond	46517	193.313	2898.322	0	141000
deposit	46517	1466.843	21667.11	0	823000
deposit_ch~g	46517	195.29	3041.988	0	144000
deposit_sa~g	46517	277.668	6077.422	0	213000
deposit_time	46517	915.527	12350.84	0	499000
loan_total	46517	1672.956	23790.34	0	704000
corecapital	46517	420.125	5120.686	-5679.297	144000

Note 1: In this event study specification, I did not include every available event time but instead select a subset of time periods that balance interpretability, statistical efficiency, and plot readability. Specifically, I dicided to include event times at 10, 5, and 2 months before adoption, as well as 2, 5, 10, and 20 months after adoption. This selection is mainly motivated by identifying Short-, Medium-, and Long-Term Effects: the selection of 2, 5, 10, and 20 months post-adoption allows to distinguish between immediate, short-run, and longer-term impacts. 2 months post-adoption captures the initial reaction to the adoption of the system. 5 and 10 months post-adoption provide insights into the short- to medium-term adjustments. 20 months post-adoption offers evidence of any persistent effects or reversals over a longer horizon.

Note 2: Unlike a traditional two-period DiD setup, where treatment and control groups have a clear, common "before" and "after" period, a staggered DiD design involves different treatment timing across units. This creates a fundamental challenge is that there is no single "Pre-Treatment" and "Post-Treatment" period for all treated units. To include summary statistics of before and after adoption for treatment and control group at the same time was not really applicable. Thus, I only included the Summary statistics for Treatment and Control group.