

Instant Payment Systems and Competition for Deposits

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Motivation and question

- **Large banks:** large deposit share, low interest rates
- **Small banks:** low deposit share, large interest rates

Motivation and question

- **Large banks:** large deposit share, low interest rates, large payment convenience
- **Small banks:** low deposit share, large interest rates, low payment convenience

Motivation and question

- **Large banks:** large deposit share, low interest rates, large payment convenience
- **Small banks:** low deposit share, large interest rates, low payment convenience
- **Instant payment systems** – often low entry costs for all banks
 - Small banks ↑ payment convenience

Question: How do instant payment systems impact competition for bank deposits?

Overview of the results 1/2

- Granular data on *Pix* in Brazil
 - Variation from the easing of COVID-19 restrictions

Overview of the results 1/2

- Granular data on *Pix* in Brazil
 - Variation from the easing of COVID-19 restrictions
- 1. Persistent reduction in deposit market concentration
 - Small banks increase deposits relative to large banks
 - Largest increase for time deposits
 - Small banks reduce interest rates relative to large banks
- 2. Increase in deposits and loans

Overview of the results 2/2

- Estimation of the IO-style framework of deposit demand and banks
3. **Increase** in **small bank** deposit demand relative to **large banks**

Overview of the results 2/2

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 - Counterfactual analysis
 4. **Absent Pix introduction**, HHI would be larger by 3%

Overview of the results 2/2

- Estimation of the IO-style framework of deposit demand and banks
3. **Increase** in **small bank** deposit demand relative to **large banks**
 - Counterfactual analysis
 4. **Absent Pix introduction**, HHI would be larger by 3%
 5. If Pix were offered **only by large banks**, HHI would be larger by 116%

Outline

- 1 Institutional setting
- 2 Data and results
- 3 Identification
- 4 Model estimation

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Instant payment systems

- Within-seconds money transfers
- Some IPS are cheap for small banks to enter (FedNOW, Pix)
- Give small banks payment convenience

IPS examples

Why Brazil?

- Third largest economy in the Americas (the largest in Latin America)
- Banking structure similar to the US:
 - Concentrated deposit markets (national HHI $\simeq$ 0.17 vs 0.2 in the US)
 - Strong community banking with many small banks
- Low but significant number of unbanked population (<7%), developed payment infrastructure

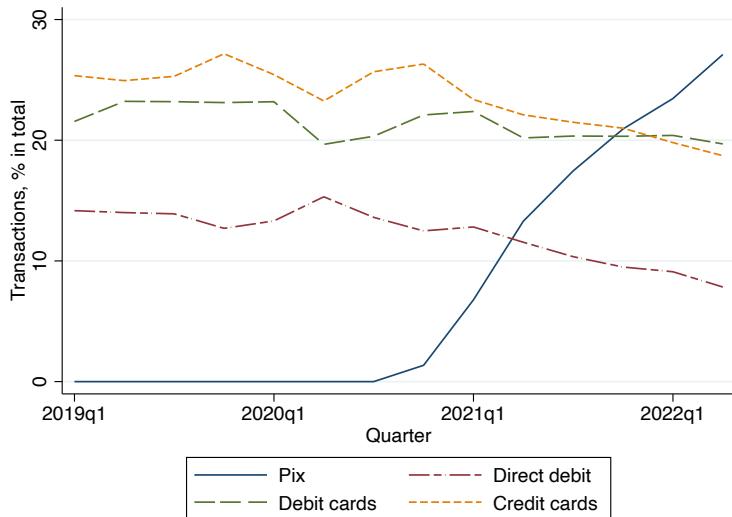
Pix in Brazil

- Launched in November 2020
- Offered by > 790 intermediaries and used by $> 120M$ people
- Free for banked households, cheap for banks and merchants (fees $\sim 0.2\%$)
- Allows making payments – **non-uniform pricing**

Other payment methods

Card fees

Electronic means of payment in Brazil, % of transactions



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Data

- Municipality-level monthly data on Pix transactions from the Central Bank of Brazil
- Branch-level monthly bank balance sheet data from ESTBAN
- Bank-level monthly personal loan rate data from the Central Bank of Brazil
- Municipality-level Census data from IBGE
- Macro variables from IPEA and Central Bank of Brazil

[Details](#)[Summary statistics](#)

Market concentration and bank size

- Herfindahl-Hirschman index for municipality deposit market concentration

$$HHI_{mt} = \sum_{i=1}^N \left(\frac{D_{imt}}{D_{mt}} \right)^2$$

Deposit betas

- Large banks – two Brazilian banks with **largest number of depositors**
 - Control >30% of all branches in Brazil and >40% of assets
 - Government is the largest stakeholder
 - Main results robust to including four largest banks

Pix relatively increases deposits of small banks

$$\log D_{imt} = \delta \cdot \log Pix_{mt} \cdot L_i + \gamma X_{imt} + \theta_t + \alpha_i + \eta_{mt} + \varepsilon_{imt}$$

	<i>Dependent variable:</i>		
	Checking deposits (1)	Saving deposits (2)	Time deposits (3)
Pix · Large	−0.030*** (0.005)	−0.032*** (0.005)	−0.043*** (0.006)
Bank FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Muni × Time FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	32,097	32,097	32,097
R ²	0.882	0.961	0.923

Standard errors are clustered at the municipality level

Impact of Boleto

Swish

HHI

Bootstrap

Deposit graph

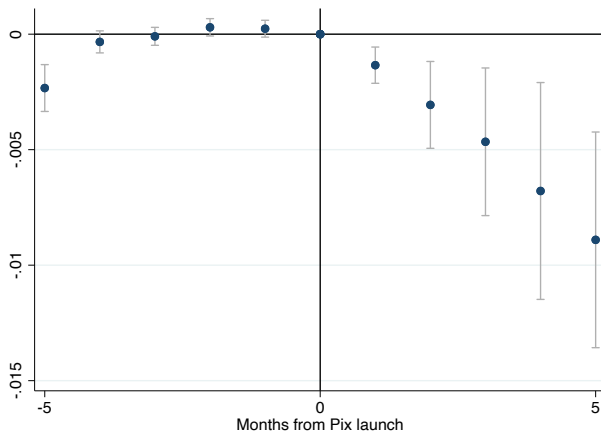
Investments

Income

Equity returns

Pix reduces deposit market concentration

$$HHI_{m,t+s} = \theta PixPerCap_{mt} + \delta HHI_{m,t-1} + \gamma X_{mt} + \eta_{mt}$$



Large banks originate riskier loans

$$\log Y_{imt} = \delta \cdot \log Pix_{mt} \cdot L_i + \gamma X_{imt} + \theta_t + \alpha_i + \eta_{mt} + o_{imt}$$

	<i>Dependent variable:</i>		
	Loans (1)	Financing (2)	Alternative funding (3)
Pix · Large	0.005 (0.004)	−0.019** (0.008)	0.198*** (0.017)
Bank FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Muni × Time FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	32,097	32,097	27,840
R ²	0.928	0.949	0.733

Standard errors are clustered at the municipality level

Investments

Equity returns

Large banks rely on uninsured financing

$$\log F_{imt} = \delta \cdot \log Pix_{mt} \cdot L_i + \gamma X_{imt} + \theta_t + \alpha_i + \eta_{mt} + o_{imt}$$

	<i>Dependent variable:</i>		
	Loans (1)	Financing (2)	Alternative funding (3)
Pix · Large	0.005 (0.004)	−0.019** (0.008)	0.198*** (0.017)
Bank FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Muni × Time FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	32,097	32,097	27,840
R ²	0.928	0.949	0.733

Standard errors are clustered at the municipality level

Investments

Equity returns

Pix relatively reduces personal loan rates of small banks

$$r_{it}^l = \delta \cdot \log \text{Pix}_{mt} \cdot L_i + \beta Y_{imt} + \gamma X_{imt} + \theta_t + \alpha_i + \varepsilon_{imt}$$

	<i>Dependent variable:</i>			
	Public loans (1)	Private loans (2)	Credit cards (3)	Auto loans (4)
Pix	−0.026*** (0.003)	−0.016*** (0.004)	−0.847*** (0.063)	−0.029*** (0.002)
Pix · Large	0.047*** (0.000)	0.016*** (0.001)	0.341*** (0.008)	0.002*** (0.000)
Bank FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	35,256	34,805	30,957	32,890
R ²	0.932	0.974	0.882	0.924

Standard errors are clustered at the municipality level

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Identification challenges

1. Reverse causality – Pix is more popular in areas with many banks

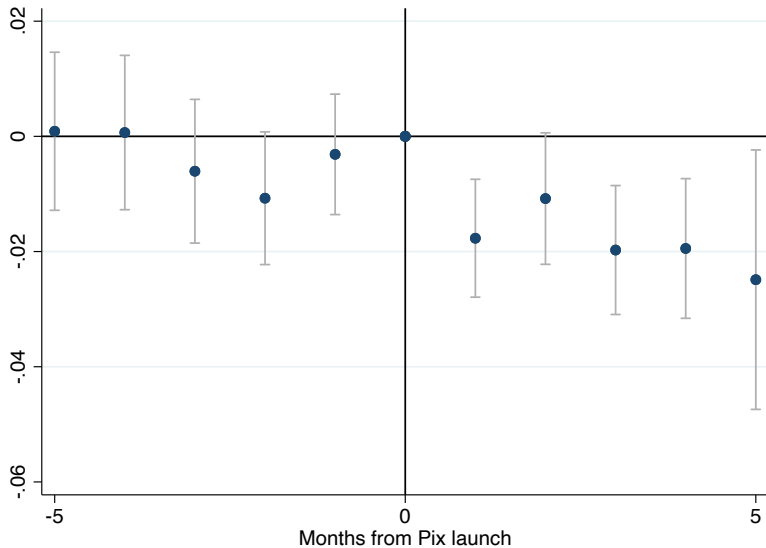
Details

2. Potential omitted variables – political beliefs unobservables, COVID stimuli, etc

Easing of COVID-19 restrictions

- Easing of COVID-19 restrictions in Brazilian municipalities by September 2020
 - *Treated* – eased restrictions, *control* – did not ease restrictions
- **Assumption:** treatment $\Rightarrow Pix_{mNov} \Rightarrow HHI_{mNov} - HHI_{mOct}$
- Heteroskedasticity-based identification – Rigobon (2003), Rigobon and Sack (2004), Hebert and Schreger (2017) [Details](#)

Pix causes a reduction in deposit market concentration



Pix increases deposits and loans

	<i>Dependent variable:</i>			
	Checking deposits (1)	Saving deposits (2)	Time deposits (3)	Total loans (4)
Pix	0.037*** (0.003)	0.014*** (0.001)	0.040*** (0.007)	0.024*** (0.002)
Controls	Yes	Yes	Yes	Yes
Observations	4,488	4,488	4,488	4,488
R ²	0.697	0.699	0.449	0.604

Cross-section

Bootstrapped errors

Standard IV

Large vs Small

Income

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Unanswered questions

- How does Pix impact deposit demand conditional on interest rates?
 - IO-style model of deposit demand
- What if Pix were **not introduced** or were available to **only** large banks?
 - Study model counterfactuals

Model set-up

- Households (mass W_t) choose to invest one dollar to one out of J banks or cash
- Banks face deposit demand and choose their deposits and assets following the equity ratio
- All banks offer instant payment systems starting from November 2020
- Banks are split into large and small based on number of depositors

Households' problem

- Households choose the best investment to maximize their utility:

$$\max_{j \in \mathcal{A}^d} u_{i,j}^t = \alpha^d r_j^t + \beta^d p_j^t + \delta^d p_j^t \ell_j + \gamma^d x_j^t + \xi_j + \varepsilon_{i,j}^t$$

- r_j^t – deposit interest rate of bank j
- p_j^t – mean of Pix values in municipalities of bank j presence
- ℓ_j – dummy for large banks
- ξ_j – product invariant quality difference (bank FEs)
- $\varepsilon_{i,j}^t$ – relation-specific shock, follows a generalized extreme-value distribution

Identification concerns

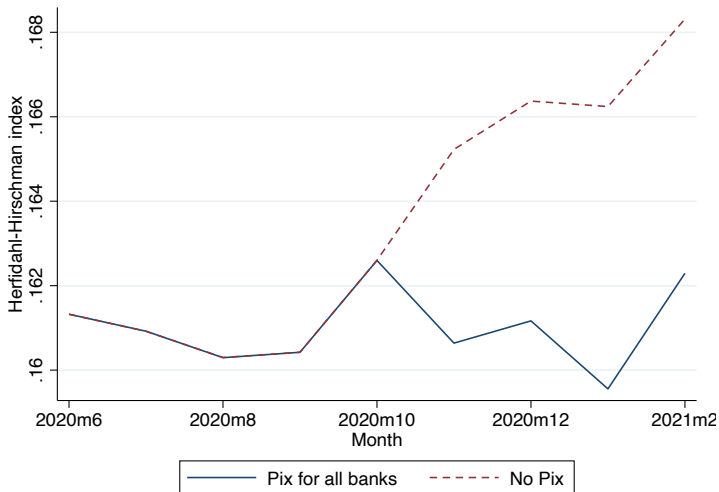
- **Identification concern 1:** interest rates are correlated with unobservable deposit demand
 - Fixed costs and provision for loan losses as instruments
- **Identification concern 2:** Pix is correlated with unobservable deposit demand
 - Use easing of COVID-19 restrictions as instruments in the first stage
 - Aggregate predicted Pix transactions to the national level

GMM estimation results

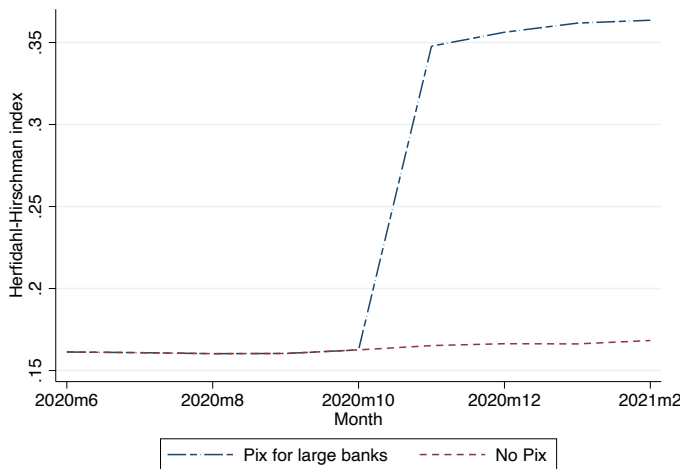
Parameter	Symbol	Estimate	Standard error
Sensitivity to deposit rates	α^d	0.80***	(0.141)
Sensitivity to Pix	β^d	0.107***	(0.025)
Additional sensitivity to Pix for large banks	δ^d	-0.023***	(0.004)
Observations		2,097	
R ²		0.980	

- 1 p.p. $\uparrow$ in deposit rates $\Rightarrow$ 0.8% $\uparrow$ in deposit share
- 1 % $\uparrow$ in Pix $\Rightarrow$ 2.3% $\uparrow$ in **small bank** deposit shares relative to **large banks**

HHI would have increased without Pix



HHI would have increased if Pix were available only to large banks



Conclusion

- Instant payment systems can promote deposit market competition
 - Implications for monetary policy, investments and access to credit
- Pix in Brazil leads to an increase in deposits and loans and a reduction in bank interest rates
 - Implications for consumers' welfare and choice of payment methods

Outline

5 Appendix

IPS examples

Country	System	Launch year	Inventor
Australia	NPP	2018	Private
Brazil	Pix	2020	Central Bank
Denmark	MobilePay	2013	Central Bank
Hong Kong	FPS	2018	Central Bank
India	UPI	2016	Central Bank
Kenya	M-Pesa	2007	Private
Sweden	Swish	2014	Private
United States	Zelle	2017	Private

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Other payment methods in Brazil

- Debit and credit cards used to be the most popular means of payment
- Boleto Bancário has been launched in 1993 for retail payments:
 - Piece of paper (now electronic) to scan in the bank app
- TED is used for wholesale payments

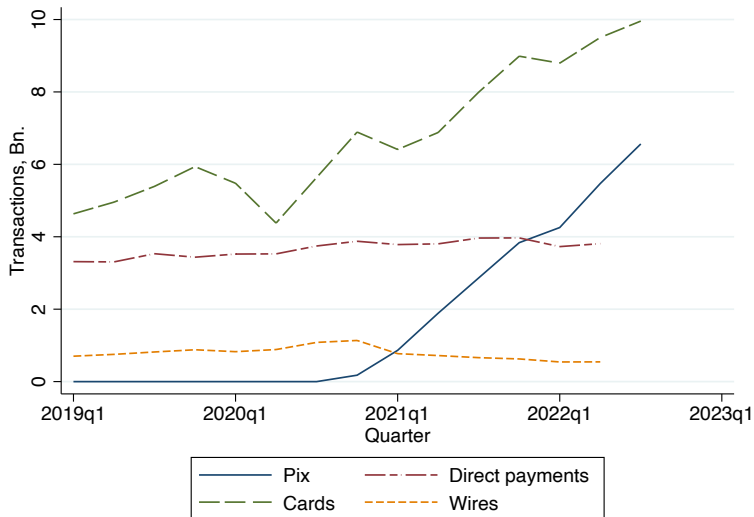
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Credit and debit card fees in Brazil

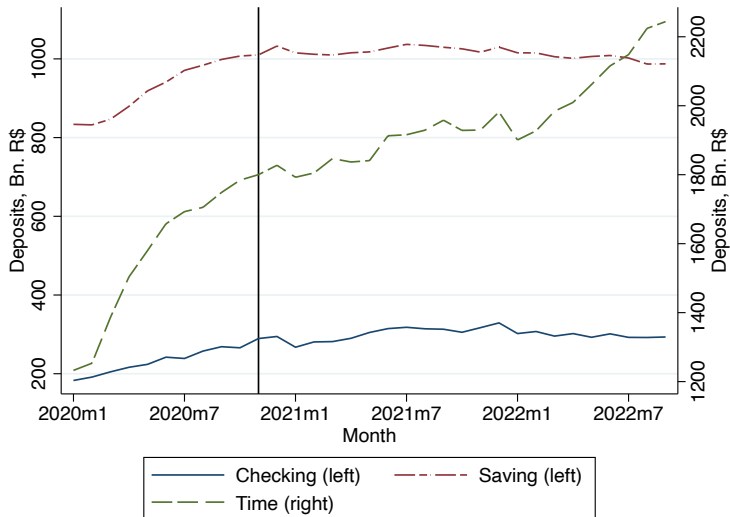
- Credit card fees are around 2.2%
- Debit card fees are around 1%
- Merchants charge customers for fees – surcharges are legal
- Paying in cash and Pix is often cheaper

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Electronic means of payment in Brazil, quantities



Deposits in Brazil



Data definitions

Name	Source	Frequency	Point of observation
Pix volume	Banco Central	Monthly	Municipality
Pix transactions	Banco Central	Monthly	Municipality
Assets	ESTBAN	Monthly	Branch
Deposits	ESTBAN	Monthly	Branch
Loans	ESTBAN	Monthly	Branch
Reserves	ESTBAN	Monthly	Branch
Loan rates	Banco Central	Monthly	Bank
Investments	IPEA	Annual	Municipality
Savings	IPEA	Annual	Municipality
GDP per capita	IBGE	Annual	Municipality
Demographics	IBGE	Only 2010	Municipality
Inflation	Banco Central	Monthly	Country
Exchange rates	Banco Central	Monthly	Country
Unemployment	Banco Central	Monthly	Country

Summary statistics

	Large banks			Small banks		
	Mean	Median	Std. dev.	Mean	Median	Std. dev.

Panel A: Before Pix launch (ESTBAN)

Checking deposits (bn. R\$)	21.1	21	5.5	0.4	0.09	1
Saving deposits (bn. R\$)	117.3	117.3	21.7	1.3	0	6
Time deposits (bn. R\$)	35.1	34.4	7.6	3.4	1.1	8.1
Total loans (bn. R\$)	58.5	58.7	11.6	2.2	0.6	4.3
Total financing (bn. R\$)	5.5	5.5	5.1	0.8	0.08	2.3
Total assets (tn. R\$)	2.9	2.8	2.4	0.1	0.02	0.3
Checking deposits (% in total)	12	12	3.3	23	8.1	33
Saving deposits (% in total)	67	67	9.2	6.2	0	18
Time deposits (% in total)	20	20	5.4	71	90	35
Observations (branch×month)		8,250			18,134	
Observations (bank×month)		4			194	

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Panel B: After Pix launch (ESTBAN)

Checking deposits (bn. R\$)	22.5	22.9	6.8	0.4	0.09	1.2
Saving deposits (bn. R\$)	120.3	120.4	22.2	1.4	0	6.3
Time deposits (bn. R\$)	35.9	36.2	9.5	***	1.1	8.7
Total loans (bn. R\$)	61.5	61.8	11.5	2.5	0.7	4.5
Total financing (bn. R\$)	5.5	5.5	5.1	0.8	0.06	2.3
Total assets (tn. R\$)	3.1	3	2.8	0.1	0.03	0.3
Checking deposits (% in total)	13	13	3.2	23	7.2	32
Saving deposits (% in total)	67	67	10	6.2	0	18
Time deposits (% in total)	20	20	6	71	88	35
Observations (branch×month)		8,250			17,985	
Observations (bank×month)		4			195	

Boleto increased deposit market concentration

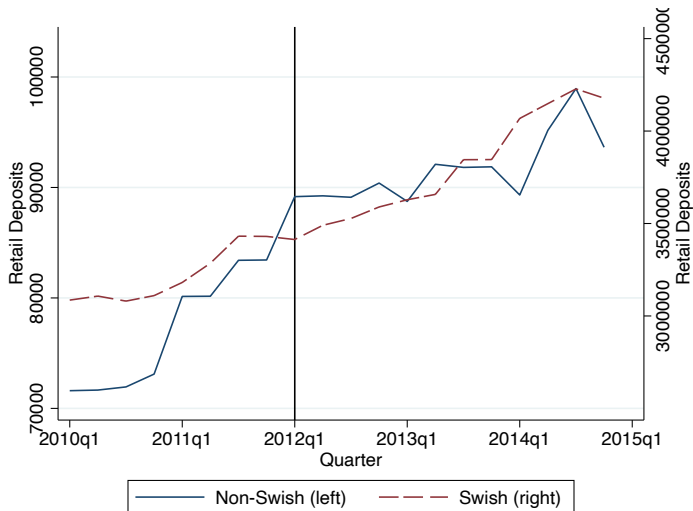
	<i>Dependent variable:</i>		
	Checking deposits (1)	Saving deposits (2)	Time deposits (3)
Boleto · Large	0.029* (0.016)	0.761*** (0.236)	−0.271*** (0.095)
Bank FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	509,088	509,088	509,088
R ²	0.894	0.860	0.812

▸ Results

▸ Additional

▸ Counterfactual

Swish increases deposit market concentration slightly


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[Counterfactual](#)

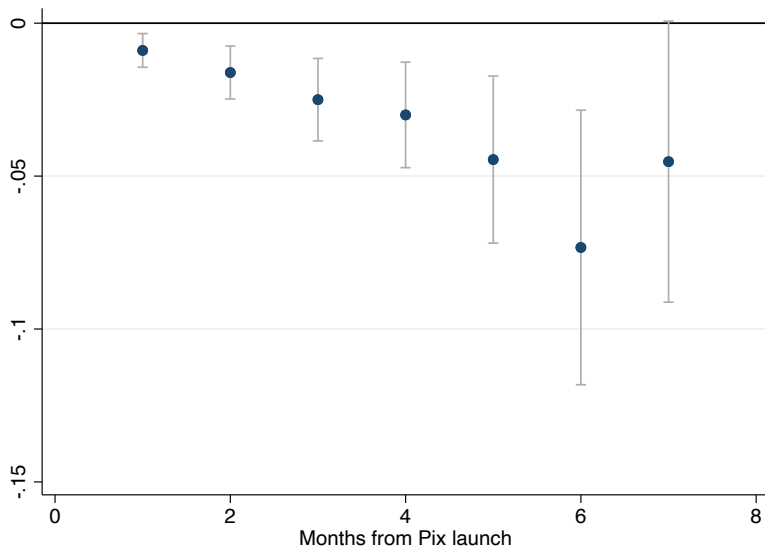
Pix impact is dampened in concentrated areas

	<i>Dependent variable:</i>					
	Checking deposits		Saving deposits		Time deposits	
	(1)	(2)	(3)	(4)	(5)	(6)
Pix	0.043 (0.027)	0.121* (0.066)	-0.078** (0.038)	-0.083 (0.090)	0.256*** (0.048)	0.699*** (0.116)
HHI	0.044** (0.018)	-0.020 (0.019)	-0.016 (0.027)	-0.064** (0.025)	-0.257*** (0.046)	-0.213*** (0.045)
Pix · Large	-0.016** (0.006)	-0.024*** (0.008)	-0.025*** (0.006)	-0.026*** (0.008)	-0.019* (0.011)	-0.047*** (0.015)
HHI · Large		0.141*** (0.013)		0.100*** (0.020)		-0.040 (0.030)
Pix · HHI		0.001 (0.011)		-0.008 (0.013)		0.069*** (0.020)
Pix · Large · HHI		0.037*** (0.007)		0.019*** (0.007)		0.041*** (0.014)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,496	36,496	36,496	36,496	36,496	36,496
R ²	0.852	0.853	0.945	0.945	0.900	0.900

Bootstrapped standard errors

	<i>Dependent variable:</i>		
	Checking deposits (1)	Saving deposits (2)	Time deposits (3)
Pix · Large	−0.030*** (0.010)	−0.032** (0.016)	−0.043*** (0.015)
Bank FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Muni × Time FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	32,097	32,097	32,097
R ²	0.882	0.961	0.923

Pix does not impact the number of bank branches



Deposit betas

- HHI does not fully capture deposit market power
 - Payment convenience itself is a non-location source of market power
- Use deposit betas: for each bank run

$$\log D_{it} = \beta \Delta i_t + \gamma X_{it} + u_{it}$$

- where i_t is a Selic rate

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Pix increases deposit betas of large banks relative to small banks

	<i>Dependent variable:</i>			
	Saving deposits		Time deposits	
	(1)	(2)	(3)	(4)
Pix	-0.018*** (0.001)	0.018*** (0.005)	-0.009*** (0.003)	0.061 (0.039)
HHI	0.000 (0.000)	0.001*** (0.000)	-0.013*** (0.002)	-0.013*** (0.003)
Large	0.015*** (0.000)	0.016*** (0.000)	0.022*** (0.007)	0.023*** (0.007)
Pix · Large	0.022*** (0.001)	0.024*** (0.000)	0.039*** (0.003)	0.043*** (0.002)
Time FE	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes
Observations	297,654	297,654	297,654	297,654
R ²	0.043	0.211	0.008	0.024

Pix is more popular in competitive areas

	<i>Dependent variable:</i>		
	Pix	Initial Pix	
	(1)	(2)	(3)
HHI	−0.107*** (0.012)	−0.107*** (0.012)	−0.0439*** (0.004)
Time FE	No	Yes	Cross-Section
Controls	Yes	Yes	Yes
Observations	6,360	6,360	3,179
R ²	0.239	0.239	0.169

Heteroskedasticity-based identification

- Consider the model of simultaneous equations:

$$P_{ix_{mt}} = \delta D_{mt} + \gamma_P F_{mt} + u_{mt}$$

$$D_{mt} = \alpha P_{ix_{mt}} + \gamma_D F_{mt} + \varepsilon_{mt}$$

Heteroskedasticity-based identification

- Consider the model of simultaneous equations:

$$PiX_{mt} = \delta D_{mt} + \gamma_P F_{mt} + u_{mt}$$

$$D_{mt} = \alpha PiX_{mt} + \gamma_D F_{mt} + \varepsilon_{mt}$$

- Standard IV:** treatment $\Rightarrow PiX_{mNov} \Rightarrow D_{mNov} - D_{mOct}$
- Assumptions on u_{mt} and ε_{mt}

Heteroskedasticity-based identification

- Consider the model of simultaneous equations:

$$Pix_{mt} = \delta D_{mt} + \gamma_P F_{mt} + u_{mt}$$

$$D_{mt} = \alpha Pix_{mt} + \gamma_D F_{mt} + \varepsilon_{mt}$$

- Standard IV:** treatment $\Rightarrow Pix_{mNov} \Rightarrow D_{mNov} - D_{mOct}$

- Assumptions on u_{mt} and ε_{mt}

First stage

- m' – treated, m^0 – control. Identification assumptions:
- $(\sigma_{m'Nov}^u)^2 - (\sigma_{m'Oct}^u)^2 > (\sigma_{m^0Nov}^u)^2 - (\sigma_{m^0Oct}^u)^2$

Heteroskedasticity-based identification

- Consider the model of simultaneous equations:

$$Pix_{mt} = \delta D_{mt} + \gamma_P F_{mt} + u_{mt}$$

$$D_{mt} = \alpha Pix_{mt} + \gamma_D F_{mt} + \varepsilon_{mt}$$

- Standard IV:** treatment $\Rightarrow Pix_{mNov} \Rightarrow D_{mNov} - D_{mOct}$
- Assumptions on u_{mt} and ε_{mt}

First stage

- m' – treated, m^0 – control. Identification assumptions:
- $(\sigma_{m'Nov}^u)^2 - (\sigma_{m'Oct}^u)^2 > (\sigma_{m^0Nov}^u)^2 - (\sigma_{m^0Oct}^u)^2$
 - $(\sigma_{m'Nov}^\varepsilon)^2 - (\sigma_{m'Oct}^\varepsilon)^2 = (\sigma_{m^0Nov}^\varepsilon)^2 - (\sigma_{m^0Oct}^\varepsilon)^2$
 - $(\sigma_{m'Nov}^F)^2 - (\sigma_{m'Oct}^F)^2 = (\sigma_{m^0Nov}^F)^2 - (\sigma_{m^0Oct}^F)^2$

COVID impact

Rigobon-Sack IV procedure

- Keep October and November in the sample
- First-stage regression:

$$PixPerCap_{mt} = \alpha Eased_m + \theta Pix_t + \gamma Eased_m Pix_t + \eta Eased_m PixPerCap_{mt} + \epsilon_{mt}$$

- $Eased_m = 1$ for treated municipalities, $Pix_t = 1$ for November 2020
- Second-stage regression:

$$HHI_{m,t+s} = \theta \widehat{PixPerCap}_{mt} + \delta HHI_{m,t} + \gamma X_{mt} + \eta_{mt}$$

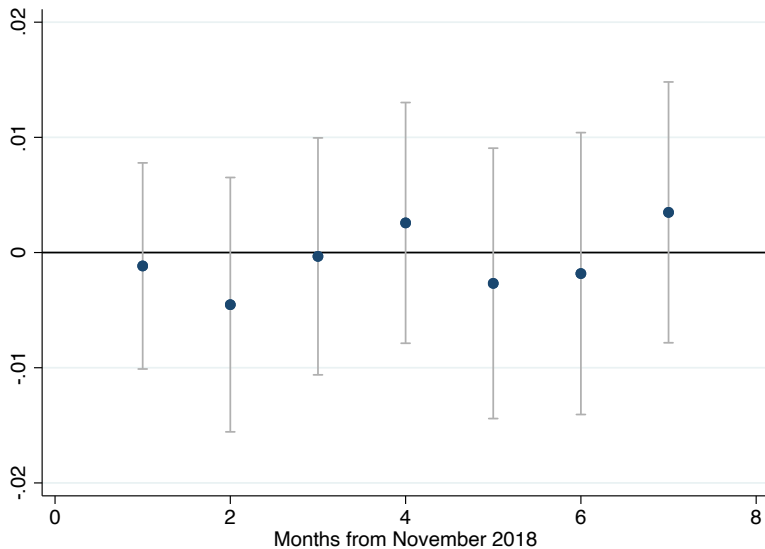
COVID restriction did not increase deposits

	<i>Dependent variable:</i>					
	Checking deposits		Saving deposits		Time deposits	
	(1)	(2)	(3)	(4)	(5)	(6)
Masks	-0.048 (0.092)		-0.152** (0.076)		-0.371 (0.287)	
Isolation		-0.098*** (0.034)		-0.014 (0.032)		-0.142 (0.129)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,326	2,331	2,326	2,331	2,326	2,331
R ²	0.773	0.774	0.792	0.793	0.486	0.487

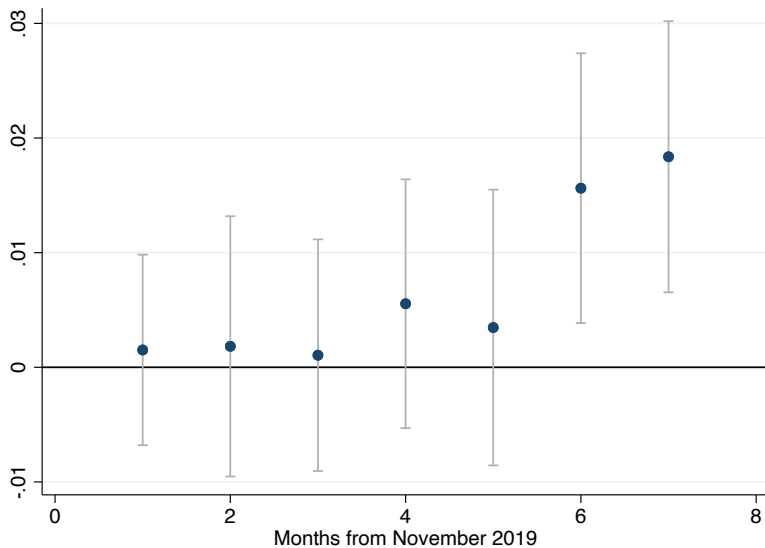
IV first-stage estimation

	<i>Dependent variable:</i>			
	Pix			
	(1)	(2)	(3)	(4)
Eased	-0.128*** (0.027)	-0.128*** (0.027)		
Post Pix	13.750*** (0.037)		13.750*** (0.041)	
Eased · Post Pix	0.357*** (0.045)	0.357*** (0.045)	0.357*** (0.050)	0.357*** (0.050)
Municipality FE	No	No	Yes	Yes
Time FE	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes
Observations	7,124	7,124	7,122	7,122
R ²	0.984	0.984	0.986	0.986

Placebo test: 2018



Placebo test: 2019



Cross-sectional Rigobon-Sack results

	<i>Dependent variable:</i>			
	Checking deposits (1)	Saving deposits (2)	Time deposits (3)	Total loans (4)
Pix	3.340*** (0.359)	2.813*** (0.337)	12.00*** (1.905)	2.889*** (0.474)
Controls	Yes	Yes	Yes	Yes
Observations	2,243	2,243	2,243	2,243
R ²	0.790	0.806	0.491	0.693

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Rigobon-Sack with bootstrapped standard errors

	<i>Dependent variable:</i>			
	Checking deposits (1)	Saving deposits (2)	Time deposits (3)	Total loans (4)
Pix	3.340*** (0.352)	2.813*** (0.332)	12.00*** (1.992)	2.889*** (0.477)
Controls	Yes	Yes	Yes	Yes
Observations	2,243	2,243	2,243	2,243
R ²	0.790	0.806	0.491	0.693

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Pix increases deposits and loans of small banks relative to large banks

	<i>Dependent variable:</i>			
	Checking deposits (1)	Saving deposits (2)	Time deposits (3)	Total loans (4)
Pix	0.062*** (0.008)	0.029*** (0.007)	0.219*** (0.031)	0.040*** (0.010)
Pix · Large	-0.057*** (0.012)	-0.036*** (0.011)	-0.371*** (0.057)	-0.035** (0.017)
Controls	Yes	Yes	Yes	Yes
Observations	7,123	7,123	7,123	7,123
R ²	0.653	0.598	0.384	0.526

Standard IV results

	<i>Dependent variable:</i>			
	Checking deposits (1)	Saving deposits (2)	Time deposits (3)	Total loans (4)
Pix	0.042*** (0.008)	0.024*** (0.007)	0.062*** (0.024)	0.021** (0.009)
Pix · Large	−0.029** (0.012)	−0.035*** (0.011)	−0.113** (0.047)	−0.005 (0.016)
Controls	Yes	Yes	Yes	Yes
Observations	7,123	7,123	7,123	7,123
R ²	0.653	0.598	0.384	0.526

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Pix does not increase GDP per capita in 2020

	<i>Dependent variable:</i>	
	HC (1)	Standard IV (2)
Pix	−0.004* (0.002)	−0.005*** (0.002)
Controls	Yes	Yes
Observations	7,124	7,124
R ²	0.426	0.426

► Deposit results

► IV results

Pix increases capital investments and savings

	<i>Dependent variable:</i>			
	Investments 2021 (1)	Investments 2020 (2)	Savings 2021 (3)	Savings 2020 (4)
Pix	0.148*** (0.0187)	0.139*** (0.0182)	0.030*** (0.00586)	−0.013*** (0.00325)
Lag	0.545*** (0.021)	0.584*** (0.018)	1.003*** (0.009)	0.925*** (0.008)
Demographic controls	Yes	Yes	Yes	Yes
Economic controls	Yes	Yes	Yes	Yes
Observations	3,152	3,166	3,089	3,178
R ²	0.727	0.756	0.984	0.994

[▶ Additional results](#)
[▶ Deposit results](#)
[▶ Loan results](#)

Large bank equity returns drop relative to small banks

	<i>Dependent variable:</i>			
	Equity returns			
	(1)	(2)	(3)	(4)
Pix	0.015*** (0.004)	0.015 (0.010)	0.015*** (0.004)	0.014 (0.010)
Large	0.003 (0.010)	0.002 (0.009)	0.0002 (0.013)	-0.0001 (0.011)
Pix · Large	-0.002 (0.015)	-0.002 (0.013)	-0.002 (0.015)	-0.001 (0.013)
Constant	-0.005* (0.003)	0.008 (0.007)	-0.002 (0.008)	0.011 (0.009)
Bank FE	No	No	Yes	Yes
Time FE	No	Yes	No	Yes
Observations	314	314	314	314
R ²	0.053	0.349	0.087	0.386

► Deposit results

► Loan results

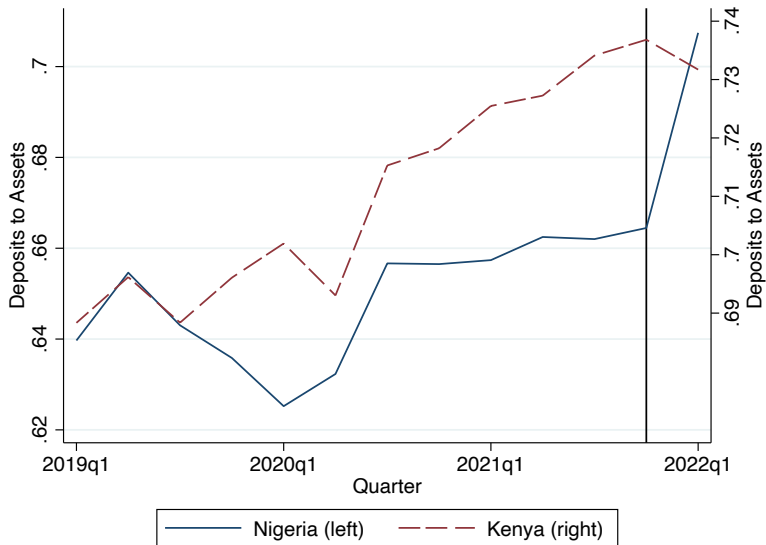
CBDC

- Central Bank Digital Currency (CBDC) is a digital analog of cash
- 90% of central banks in the world consider CBDC, two already adopted one
- Main concern is that households will prefer CBDC to bank deposits – **crowding-out effect** which in turn leads to a **contraction in lending**
- Literature claims that CBDC will crowd out bank deposits
- CBDC is an instant payment system as well

Data

- Nigeria is the largest country to have launched CBDC – e-Naira in October 2021
- Hand-collect banking data from Nigeria
- Hand-collect banking data from Kenya to compare two neighboring countries

CBDC increases deposits in Nigeria



Households

- Choose consumption and deposits to maximize their utility

$$U_0^i = \sum_{t=0}^T \log C_t^i$$

subject to

$$C_t^i + DL_{t+1}^i + DS_{t+1}^i \leq Y_t^i + DL_t^i(1 + r_t^{d\ell}) + DS_t^i(1 + r_t^{ds})$$

Households

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$$C_t^i + DL_{t+1}^i + DS_{t+1}^i \leq Y_t^i + DL_t^i(1 + r_t^{d\ell}) + DS_t^i(1 + r_t^{ds})$$

$$\eta C_t^i \leq DL_t^i + \varepsilon_t^i DS_t^i$$

- η – share of goods that require large bank deposits, ε_t^i is an iid shock with support $[0, \varepsilon^u)$

Timeline

1. Decide on composition of portfolio
 2. ε^i is realized
 3. Decide on consumption
- Such structure results in **precautionary savings**

Banks

- Both large and small banks choose deposits and loans to maximize their value

$$V(D_t^b, L_t^b) = \max_{D_{t+1}^b, L_{t+1}^b} \phi N_t^b + \beta \mathbb{E}_t V(D_{t+1}^b, L_{t+1}^b)$$

where $N_t = L_t - D_t$

subject to the budget constraint

$$(1 - \phi)N_t^b \geq \frac{1}{1 + r_{t+1}^{\ell b}} L_{t+1}^b - \frac{1}{1 + r_{t+1}^{db}} D_{t+1}^b$$

and leverage constraint

$$\frac{1}{1 + r_{t+1}^{db}} D_{t+1}^b \leq \xi \frac{1}{1 + r_{t+1}^{\ell b}} L_{t+1}^b$$

Instant payment system

- Instant payment system can be launched with two designs:
 - ① Available to all banks (like Pix)
 - ② Available to large banks (like Zelle and Swish)
- If IPS is available only to large banks, **it does not impact deposits**
 - **Increase in deposit market concentration** in the model with cash

Economy with cash

Cashless economy results

Proposition

In partial equilibrium, i.e., with fixed interest rates and exogenous endowment, Y_t , increase in support of ε_t^i from $[0, \varepsilon^u)$ to $(\varepsilon^l, 1]$ in the evening of the preceding period leads to an increase in DS_t relative to DL_t .

Cashless economy results

Proposition

In partial equilibrium, i.e., with fixed interest rates and exogenous endowment, Y_t , increase in support of ε_t^i from $[0, \varepsilon^u)$ to $(\varepsilon^l, 1]$ in the evening of the preceding period leads to an increase in DS_t relative to DL_t .

- Reduction in deposit market concentration

Economy with cash

Interest rates

Proposition

Assume an increase (or no change) in $\frac{DS_t^i}{DL_t^i}$ for all households and an increase for at least one household. Then, the following holds:

- ① reduction in $r_t^{ds} - r_t^{dl}$;
- ② increase in $\frac{L_t^s}{L_t^l}$;
- ③ reduction in $r_t^{\ell s} - r_t^{\ell l}$.

Interest rates

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Assume an increase (or no change) in $\frac{DS_t^i}{DL_t^i}$ for all households and an increase for at least one household. Then, the following holds:

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- ③ reduction in $r_t^{\ell s} - r_t^{\ell l}$.

- Small banks pay relatively lower deposit rates and charge relatively lower loan rates

Model predictions

- ① Instant payment systems available to all banks **reduce** deposit market concentration
 - Magnitudes depend on available functions and mitigated frictions
- ② Spreads between interest rates of small and large banks **shrink**
- ③ Deposits and loans **increase**
- ④ Instant payment systems available only to large banks **increase** deposit market concentration

Model with cash

- Choose consumption and deposits to maximize their utility

$$U_0^i = \sum_{t=0}^T \log C_t^i$$

subject to

$$C_t^i + DL_{t+1}^i + DS_{t+1}^i + M_{t+1}^i \leq Y_t^i + DL_t^i(1 + r_t^{d\ell}) + DS_t^i(1 + r_t^{ds}) + M_t^i$$

Model with cash

- Choose consumption and deposits to maximize their utility

$$U_0^i = \sum_{t=0}^T \log C_t^i$$

subject to

$$C_t^i + DL_{t+1}^i + DS_{t+1}^i + M_{t+1}^i \leq Y_t^i + DL_t^i(1 + r_t^{dl}) + DS_t^i(1 + r_t^{ds}) + M_t^i$$

$$\eta^\ell C_t^i \leq M_t + u_t^i DL_t^i$$

$$\eta^s C_t^i \leq M_t + DL_t^i + \varepsilon_t^i DS_t^i$$

- ε_t^i and u_t^i are iid shocks with supports $[0, \varepsilon^u)$ and $[0, u^u)$

Timeline

1. Decide on composition of portfolio
2. ε^i and u^i are realized
3. Decide on consumption
 - Such structure results in **precautionary savings** of cash and large bank deposits

► Back

Results for the economy with cash

Proposition

In partial equilibrium, i.e., with fixed interest rates and exogenous endowment, Y_t ,

- ① *increase in support of ε_t^i from $[0, \varepsilon^u)$ to $(\varepsilon^l, 1]$ in the evening of the preceding period leads to an increase in DS_t relative to DL_t and M_t ;*
- ② *increase in support of ε_s^i from $[0, \varepsilon^u)$ to $(\varepsilon^l, 1]$ in the evening of the preceding where $s > t$ leads to an increase in DS_t relative to DL_t if the horizon of the model is finite;*
- ③ *increase in support of u_t^i from $[0, u^u)$ to $(u^l, 1]$ in the evening of the preceding period leads to an increase in DL_t relative to DS_t and M_t ;*
- ④ *increase in support of u_t^i from $[0, u^u)$ to $(u^l, 1]$ in the evening of the preceding period where $s > t$ leads to an increase in DL_t relative to DS_t and M_t if the horizon of the model is finite.*