High-Speed Internet, Financial Technology and Banking

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Bocconi University

BIS-BoE-CEPR Workshop

September 2020

Financial Technology & Banking

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Swift Recap: FinTechs change bank business

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Swift Recap: FinTechs change bank business *"outside"* the bank

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Bank
Liquidity

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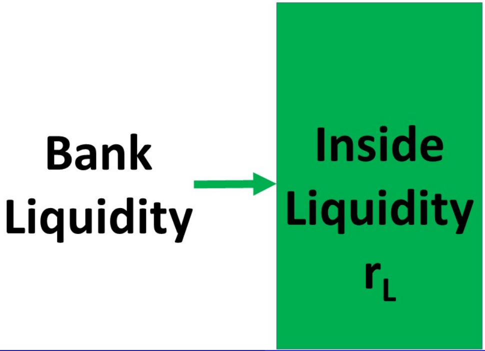

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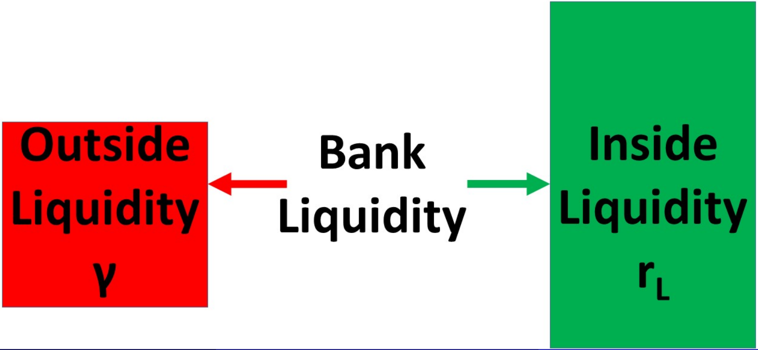

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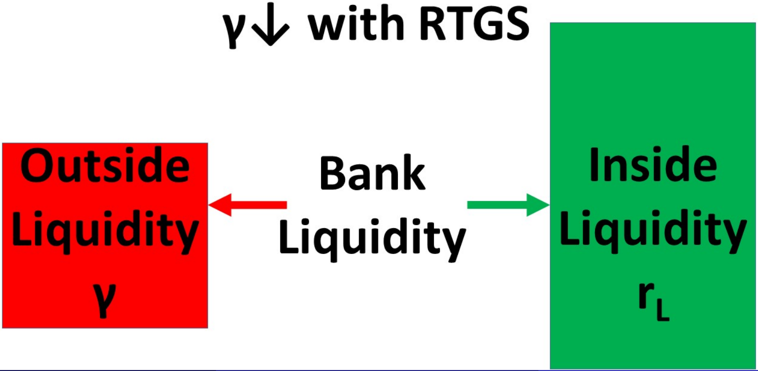

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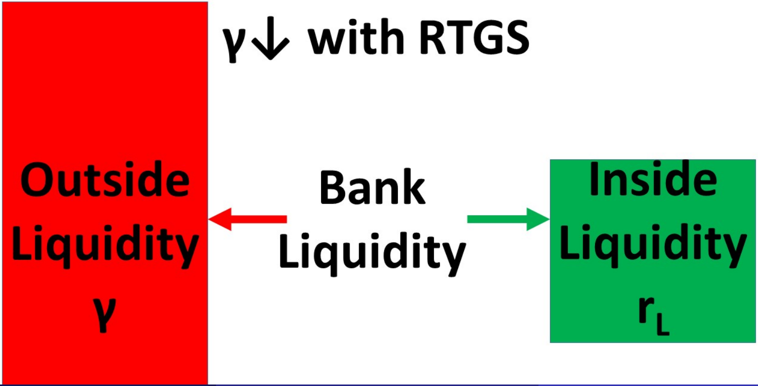

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$*$ Event Study & D-i-D $\rightarrow$ *country-level variation*

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Natural Experiment → RTGS & Staggering of the Submarine Fiber-Optic Cable in Africa

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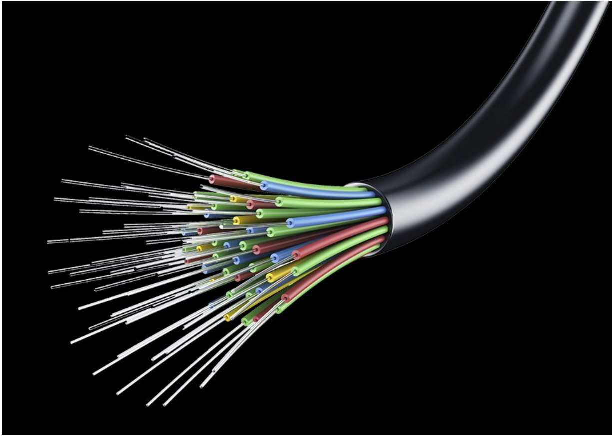
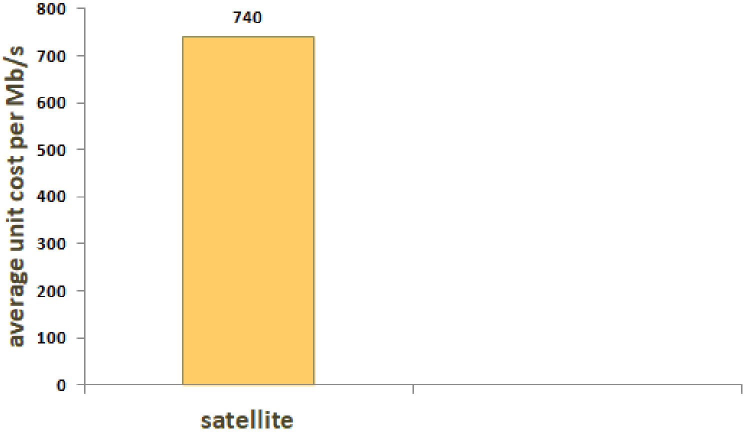


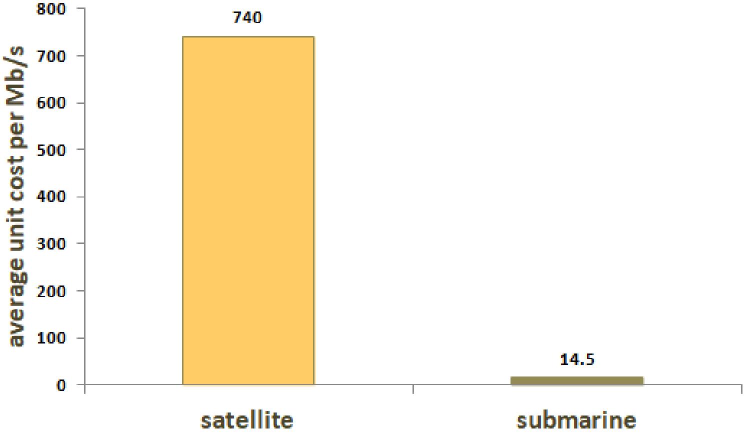
Submarine Cable $\rightarrow$ RTGS connection cost **98%**$\downarrow$

Submarine Cable → RTGS connection cost **98%↓**



Note: Average unit cost per Mb/s (Detecon, 2013)

Submarine Cable → RTGS connection cost **98%**↓



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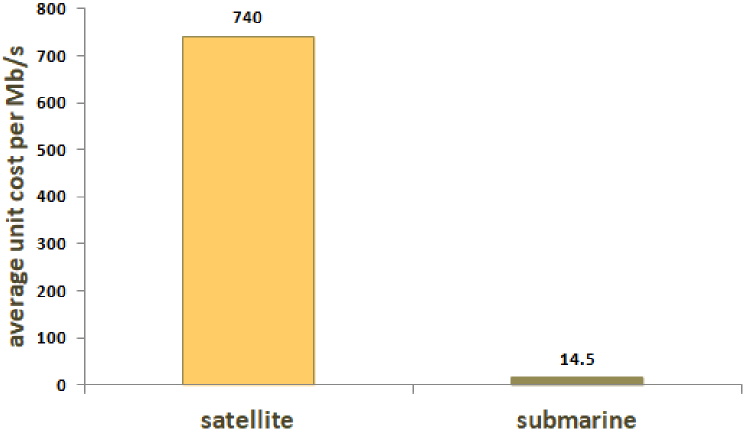
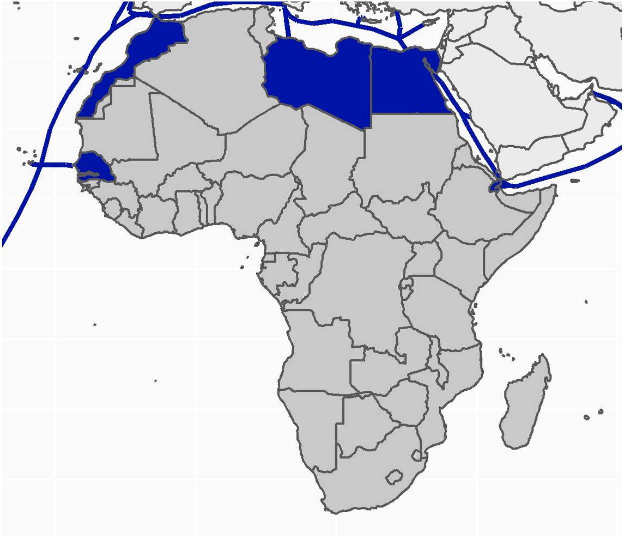
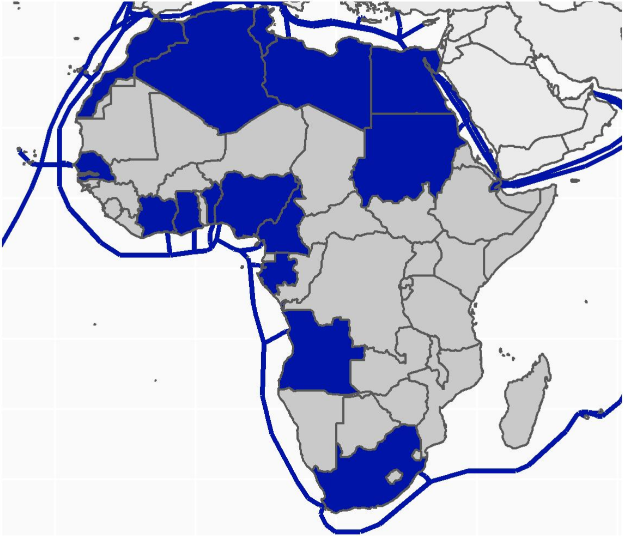


Note: Average unit cost per Mb/s (Detecon, 2013) - **how did the submarine cable staggering take place?**

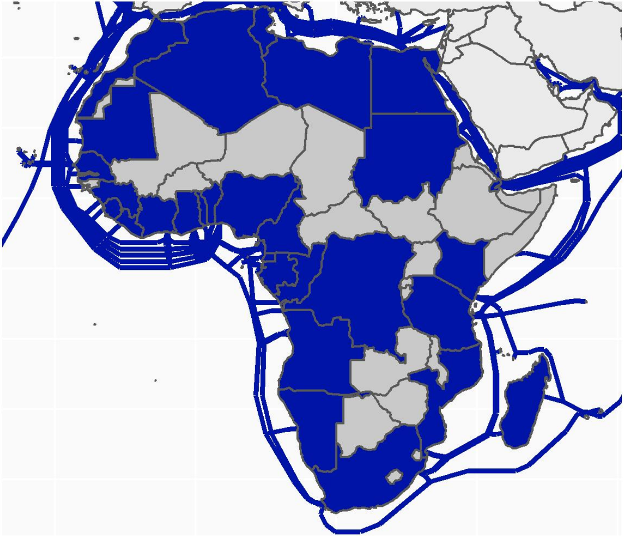
2000



2005



2012 - All cables



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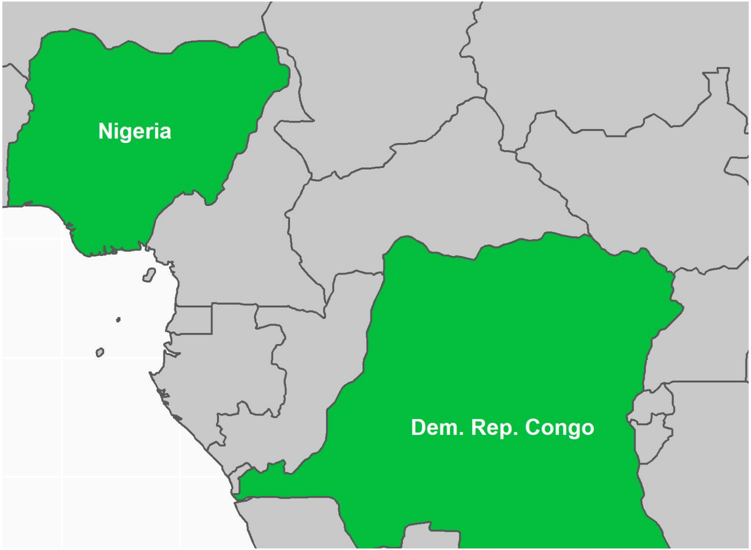
Exploit Country vs Group Connectedness

Example: Access bank



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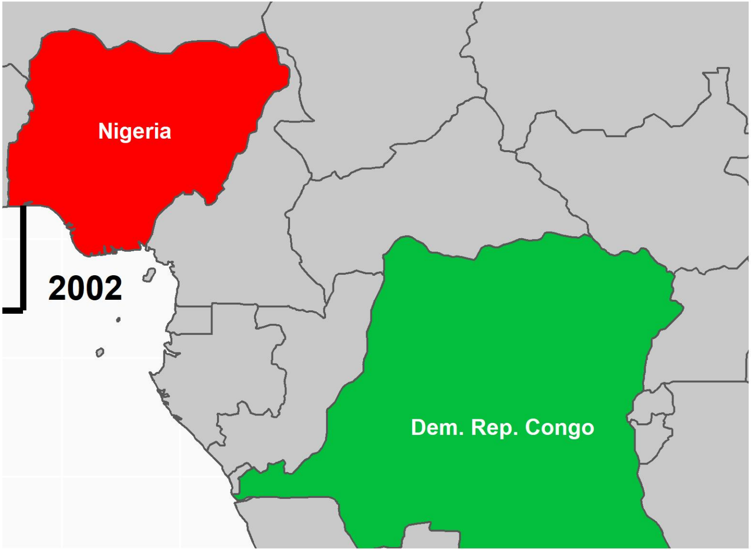

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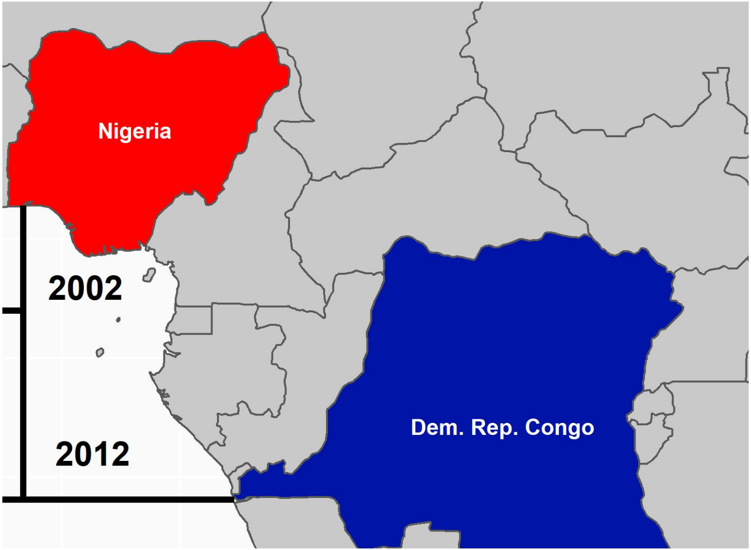

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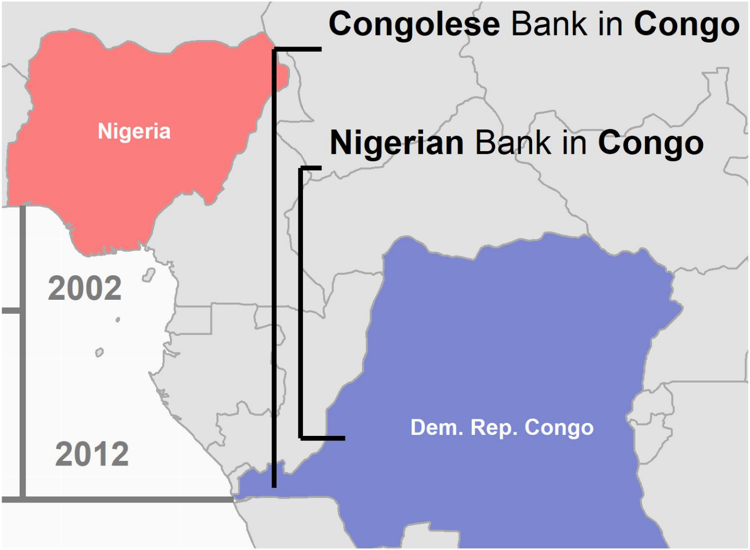

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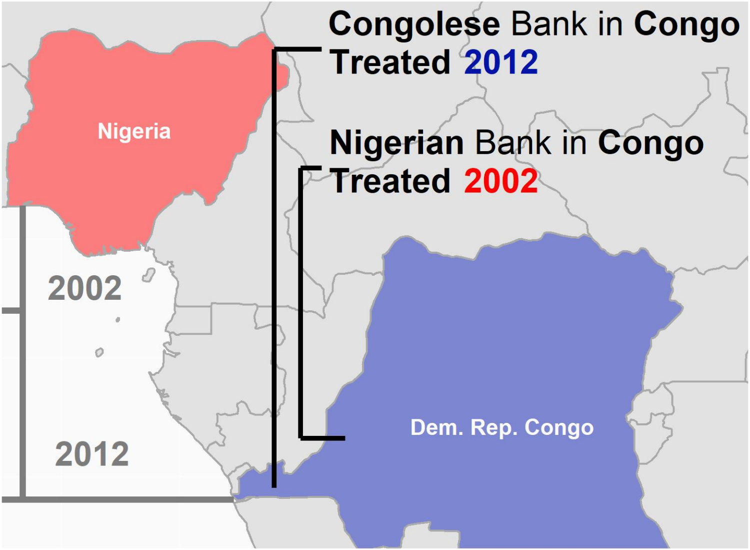

Literature

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Liquidity and Interbank Markets

∗ Diamond and Dybvig, 1983; Bencivenga & Smith, 1991; Diamond and Rajan, 2001; Kashap et al., 2002; Goldstein and Pauzner, 2005;

∗ Interbank Markets - Townsend, 1979, Diamond, 1984; Allen and Gale, 2000; Heider, Hoerova & Holthausen, 2015, Allen et al., 2018; Craig and Ma, 2019; Coen & Coen, 2019

A Roadmap

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1. Interbank Markets & Submarine Cables

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2. Data, Machine-Learning & Empirics

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3. Robustness Checks

Interbank Markets and Submarine Cables

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Data, Machine-Learning & Empirics

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Quality check: 1 correlation with confidential data from 4 countries

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Top performer: **Bagging** (75%). Mean: 0.466 (0.499).

Empirical Analysis

Event Study

Event Study + Staggered Diff-in-Diff

$$Y_{ict} = \alpha_i + \beta_t + \sum_{k=-5}^{5} \gamma_K I \left\{ K_{ct} = k \right\} + \varepsilon_{ict}$$

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RTGS Adoption - **Country** Level ↑

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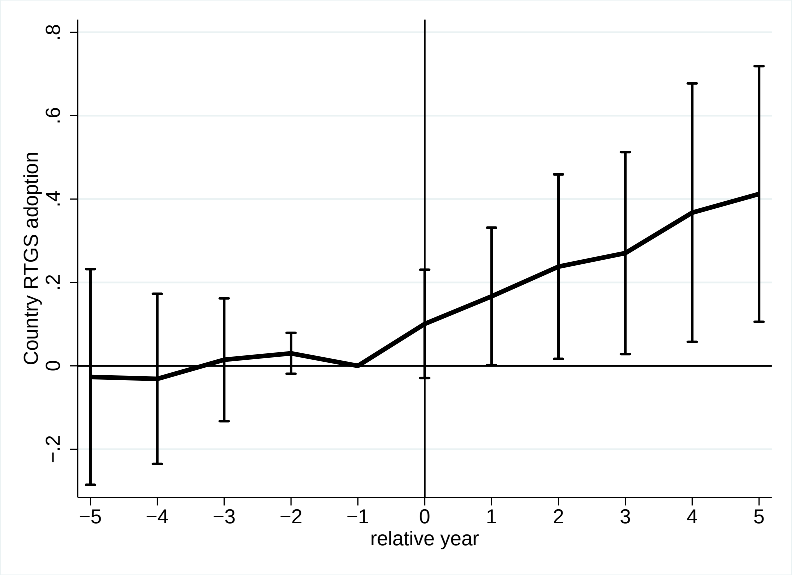

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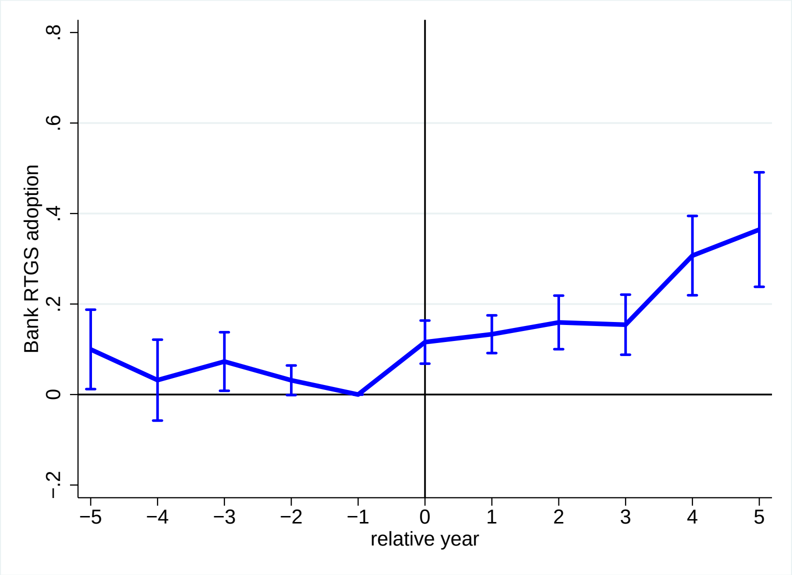

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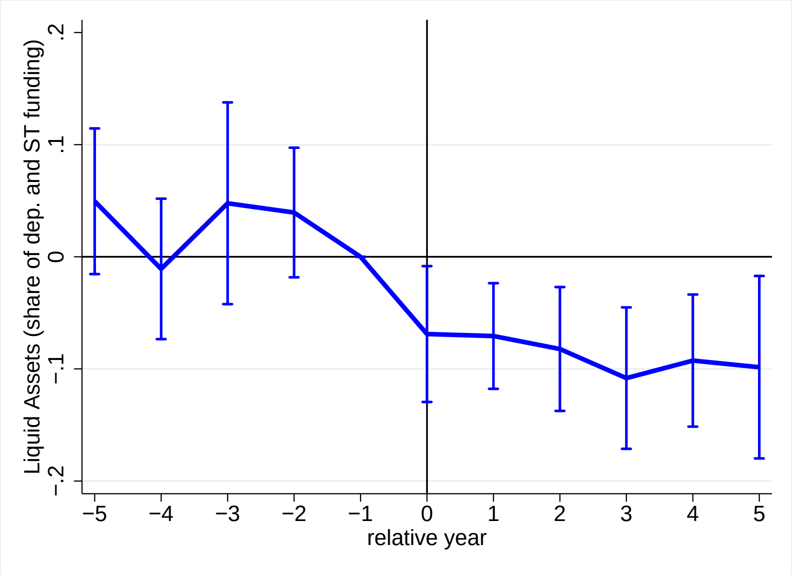

Interbank Assets $\uparrow$

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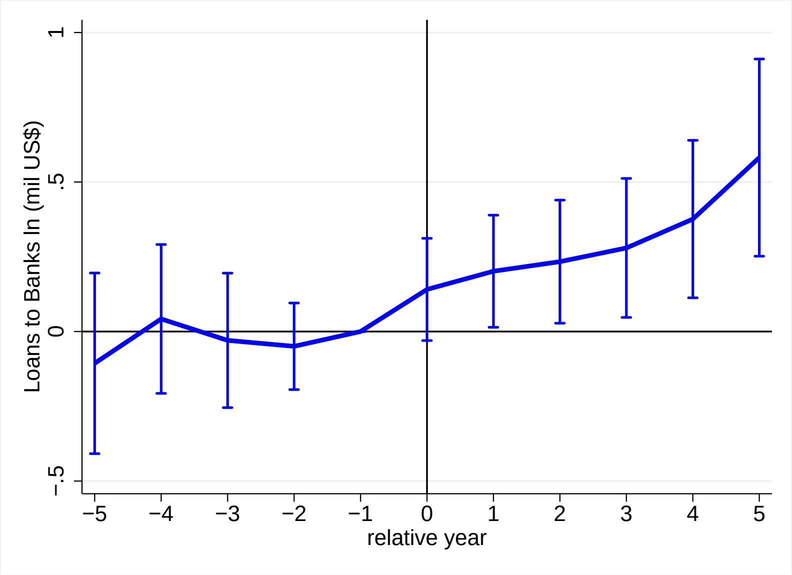

Interbank Liabilities $\uparrow$

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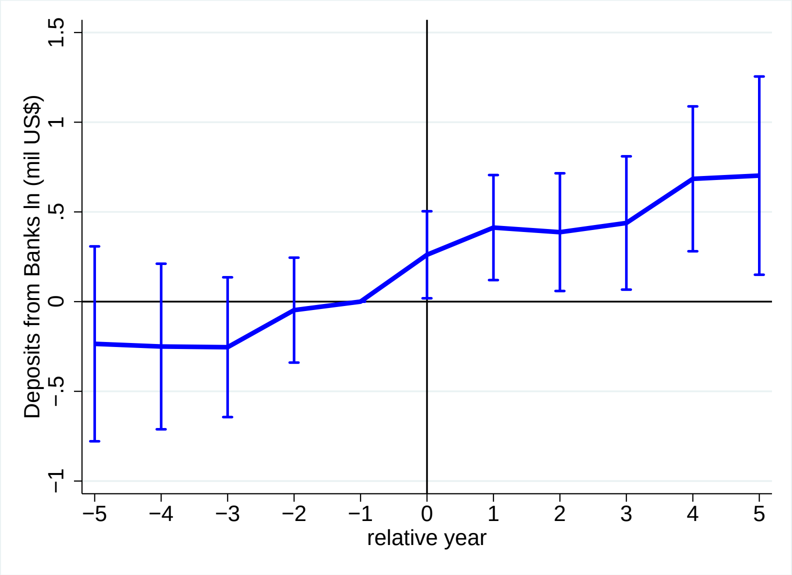

Lending $\uparrow$

Lending ↑

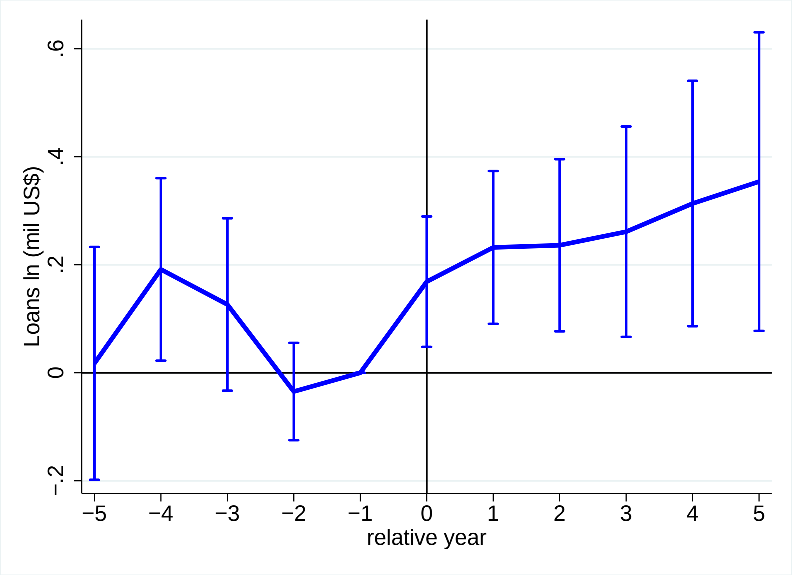

Table 2: Staggered Diff-in-Diff and RTGS adoption

Variables	(1) RTGS Country-Level	(2) RTGS Bank-Level
$Submarine_{ct}$	0.141*	0.0642***
	(0.079)	(0.0241)
Country FE	Yes	No
Bank FE	No	Yes
Year FE	Yes	Yes
Obs.	466	3863
Adj. R^2	0.652	0.772
M.D.V.	0.405	0.468

Notes: Standard errors in parentheses, clustered at country level in (1) and bank level in (2)

Table 3: Staggered Diff-in-Diff and Banking

	Liquid Assets (share DST)	Loans to Banks ln(milUS$)	Deposits from Banks ln(milUS$)	Priv.Sector Loans ln(milUS$)
$Submarine_{ct}$	-0.0961***	0.139	0.411***	0.157**
	(0.0220)	(0.0894)	(0.132)	(0.0687)
Obs.	3837	3536	2754	3821
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.430	0.828	0.715	0.891
M.D.V.	0.463	3.744	2.690	4.872

Notes: Standard errors in parentheses, clustered at bank level

Staggered Diff-in-Diff + Heterogeneity

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$$Y_{ict} = \alpha_i + \beta_t + \gamma_1 D_{ct} \times \mathbf{X_i} + \gamma_2 D_{ct} + \varepsilon_{ict}$$

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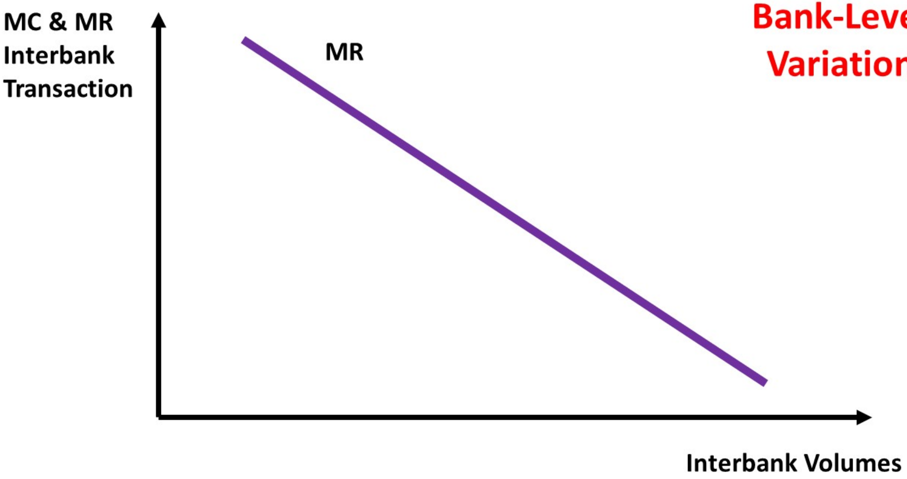
What is the interpretation of this?



Bank-Level Variation

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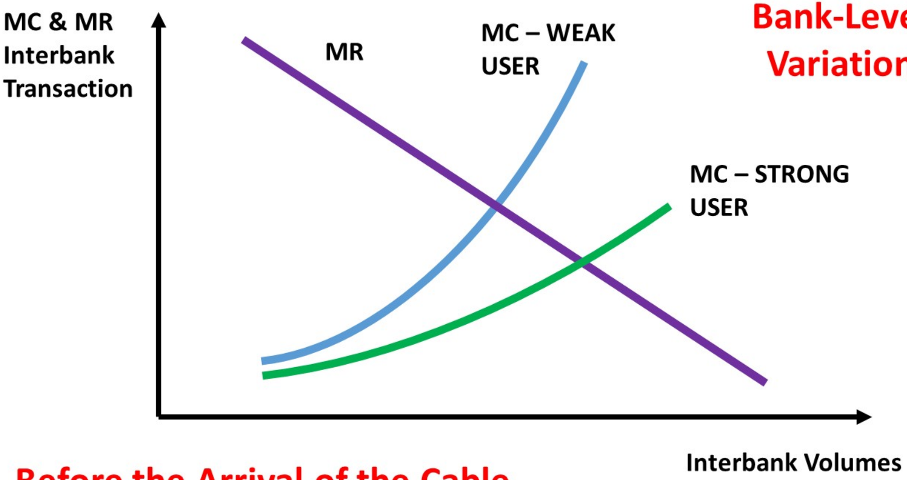
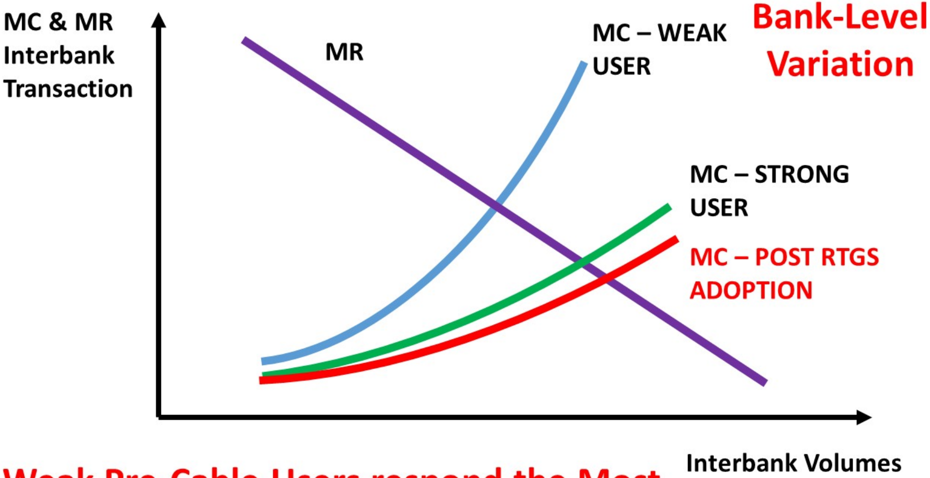


Before the Arrival of the Cable



Weak Pre-Cable Users respond the Most

Table 4: Heterogeneity and Banking

	Liquid Assets (share DST)	Loans to Banks ln(milUS$)	Deposits from Banks ln(milUS$)	Priv.Sector Loans ln(milUS$)
$Submarine_{ct}$	-0.049*	-0.080	0.052	-0.0401
	(0.025)	(0.111)	(0.148)	(0.0944)
$Submarine_{ct}$ ×	-0.099***	0.447***	0.772***	0.378***
$Weak_{iT_{PRE}}$	(0.033)	(0.162)	(0.221)	(0.121)
Obs.	3720	3514	2710	3715
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.475	0.830	0.717	0.892
M.D.V.	0.463	3.744	2.690	4.872

Notes: Standard errors in parentheses, clustered at bank level.

Table 4: Heterogeneity and Banking

	Liquid Assets (share DST)	Loans to Banks ln(milUS$)	Deposits from Banks ln(milUS$)	Priv.Sector Loans ln(milUS$)
$Submarine_{ct}$	-0.049*	-0.080	0.052	-0.0401
	(0.025)	(0.111)	(0.148)	(0.0944)
$Submarine_{ct}$ $\times$	-0.099***	0.447***	0.772***	0.378***
$Weak_{iT_{PRE}}$	(0.033)	(0.162)	(0.221)	(0.121)
Obs.	3720	3514	2710	3715
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.475	0.830	0.717	0.892
M.D.V.	0.463	3.744	2.690	4.872

Notes: Standard errors in parentheses, clustered at bank level.

Heterogeneity is robust to **Country-Year FEs**

Demand vs Supply

Demand vs Supply - replace D_{ct} with D_{gt}

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$$Y_{igct} = \alpha_i + \beta_t + \gamma D_{gt} + \psi_1 D_{gt} \times \mathbf{X_{ic}} + \varepsilon_{igct}$$

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$$Y_{igct} = \alpha_i + \beta_t + \gamma D_{gt} + \psi_1 D_{gt} \times \mathbf{X_{ic}} + \varepsilon_{igct}$$

Identifying HP: demand shock not differential across banks within the *same group (country) and year* & with weak/strong usage ex ante

Table 6: Internet and the Supply of Liquidity

	Liquid Assets (share DST)	Loans to Banks ln(milUS$)	Deposits from Banks ln(milUS$)	Priv.Sector Loans ln(milUS$)
$Submarine_{gt}$ ×	-0.0253	-0.103	0.209	0.131*
	(0.0224)	(0.117)	(0.147)	(0.0714)
$Submarine_{gt}$ ×	-0.0847**	0.364***	0.623***	0.231**
$Weak_{iT_{PRE}}$	(0.0373)	(0.135)	(0.191)	(0.0930)
Obs.	3720	3514	2710	3715
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.471	0.829	0.716	0.892
M.D.V.	0.461	3.750	2.696	4.933

Notes: Standard errors in parentheses, clustered at bank level

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Bank FE	Yes	Yes	Yes	Yes
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M.D.V.	0.461	3.750	2.696	4.933

Notes: Standard errors in parentheses, clustered at bank level

Heterogeneity is robust to **Group-Year FEs** & **Country-Year FEs**

Firms

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$$Y_{fct} = \alpha_c + \beta_t + \gamma_1 D_{ct} \times \mathbf{X_c} + \gamma_2 D_{ct} + \varepsilon_{it}$$

Table 9: Firms, Cables and Interbank Markets

Variables	Access Finance Dummy	Bank Credit Dummy	Sale ln(USD)	Workforce ln(N)	Maturities ln(Months)
$Submarine_{ct}$	0.043	-0.001	0.185	-0.231	0.587**
	(0.061)	(0.047)	(1.108)	(0.202)	(0.214)
$Submarine_{ct}$ $\times$	0.160**	0.097**	3.158**	0.356**	0.418*
$Weak_{cT_{PRE}}$	(0.065)	(0.035)	(1.173)	(0.148)	(0.238)
Country FE	Yes	Yes	Yes	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	25389	25222	24314	12637	1139
Adj. R sq.	0.0965	0.127	0.362	0.129	0.127
M.D.V.	0.638	0.211	16.43	3.198	3.008

Notes: Standard errors in parentheses, clustered at country level

Robustness Checks

Robustness Checks

Robustness Checks

1. Include landlocked countries
2. Longer bank dataset (2000 to 2018) - $\neq$ datasets
3. Restrict a bank & firm sample
4. Re-offer bank evidence with country FEs
5. Account for observables - bank & country controls, bank evidence
6. Cluster bank regressions at country & country-year link
7. Account for observables - country controls, firm evidence1
8. Many more (event study with 3-year window etc etc etc).

Concluding Remarks

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Thank You

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Table E1: Staggered Diff-in-Diff - Landlocked countries

Variables	(I) Liquid Assets (share DST)	(II) Loans to Banks ln(milUS$)	(III) Deposits from Banks ln(milUS$)	(IV) Private loans ln(milUS$)
$Submarine_{ct}$	-0.0808***	0.158*	0.362***	0.109*
	(0.0199)	(0.0891)	(0.126)	(0.0633)
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	4983	4615	3519	4978
Adj. R^2	0.422	0.809	0.696	0.892
M.D.V.	0.458	3.565	2.535	4.684

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Table E2: Staggered Diff-in-Diff - Updated Sample

Variables	(I) Liquid Assets (share DST)	(II) Loans to Banks ln(milUS$)	(III) Deposits from Banks ln(milUS$)	(IV) Private loans ln(milUS$)
$Submarine_{ct}$	-0.0874***	0.194**	0.455***	0.181**
	(0.0197)	(0.0949)	(0.147)	(0.0809)
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	5389	5077	4029	5379
Adj. R^2	0.364	0.763	0.663	0.864
M.D.V.	0.444	3.820	2.860	5.104

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Table E3: Staggered Diff-in-Diff - Restricted Sample

Variables	(I) Liquid Assets (share DST)	(II) Loans to Banks ln(milUS$)	(III) Deposits from Banks ln(milUS$)	(IV) Private loans ln(milUS$)
$Submarine_{ct}$	-0.114***	0.291**	0.743***	0.336***
	(0.0229)	(0.134)	(0.176)	(0.104)
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	1415	1415	1415	1415
Adj. R^2	0.618	0.865	0.769	0.939
M.D.V.	0.376	4.205	3.046	5.631

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Table I1: Staggered Diff-in-Diff - Firms Restricted Sample

Variables	(I) Access Finance (dummy)	(II) Bank Credit (dummy)	(III) Sales ln(USD)	(IV) Maturity ln(Months)
$Submarine_{ct}$	0.159***	0.134**	2.290	0.862***
	(0.0384)	(0.0530)	(1.780)	(0.273)
Country FE	Yes	Yes	Yes	No
Year FE	Yes	Yes	Yes	Yes
Obs.	20032	20032	19811	1010
Adj. R^2	0.0929	0.124	0.280	0.118
M.D.V.	0.635	0.240	12.16	3.050

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Table G1: Staggered Diff-in-Diff Country Fixed Effects

Variables	(I) Liquid Assets (share DST)	(II) Loans to Banks ln(milUS$)	(III) Deposits from Banks ln(milUS$)	(IV) Private loans ln(milUS$)
$Submarine_{ct}$	-0.0965***	0.195*	0.353**	0.198**
	(0.0226)	(0.0999)	(0.147)	(0.0901)
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	3861	3565	2794	3845
Adj. R^2	0.166	0.392	0.324	0.449
M.D.V.	0.466	3.735	2.675	4.861

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Table F4: Staggered Diff-in-Diff - All controls

Variables	(I) Liquid Assets (share DST)	(II) Loans to Banks ln(milUS$)	(III) Deposits from Banks ln(milUS$)	(IV) Private loans ln(milUS$)
$Submarine_{ct}$	-0.0820***	0.130	0.431***	0.0921
	(0.0227)	(0.0992)	(0.130)	(0.0682)
Controls:				
Country indicators	Yes	Yes	Yes	Yes
Regulatory quality	Yes	Yes	Yes	Yes
Bank indicators	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	3538	3244	2561	3512
Adj. R^2	0.425	0.835	0.730	0.913
M.D.V.	0.458	3.788	2.792	4.048

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Table H2: Staggered Diff-in-Diff - Cluster country

	(I)	(II)	(III)	(IV)
Variables	Liquid Assets (share DST)	Loans to Banks ln(milUS$)	Deposits from Banks ln(milUS$)	Private loans ln(milUS$)
$Submarine_{ct}$	-0.0961***	0.139	0.411**	0.157
	(0.0336)	(0.115)	(0.197)	(0.140)
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	3837	3536	2754	3821
Adj. R^2	0.430	0.828	0.715	0.891
M.D.V.	0.463	3.744	2.690	4.872

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Table H3: Staggered Diff-in-Diff - Cluster country-year

Variables	(I) Liquid Assets (share DST)	(II) Loans to Banks ln(milUS$)	(III) Deposits from Banks ln(milUS$)	(IV) Private loans ln(milUS$)
$Submarine_{ct}$	-0.0961***	0.139*	0.411***	0.157*
	(0.0236)	(0.0744)	(0.124)	(0.0810)
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	3837	3536	2754	3821
Adj. R^2	0.430	0.828	0.715	0.891
M.D.V.	0.463	3.744	2.690	4.872

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Table I2: Staggered Diff-in-Diff - Weak Interbank, Country controls

Variables	(I) Access Finance (dummy)	(II) Bank Credit (dummy)	(III) Sales ln(USD)	(IV) Maturity ln(Months)
Submarine$_{ct}$	-0.203	-0.0517	-0.075	-0.289
	(0.120)	(0.0935)	(1.656)	(0.289)
Submarine	0.279***	0.196***	3.305**	0.629**
$\times$ *Weak Intb*$_{ct}$	(0.0770)	(0.0587)	(1.557)	(0.242)
Controls:				
Country indicators	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	No
Year FE	Yes	Yes	Yes	Yes
Obs.	22696	22550	21867	1139
Adj. R^2	0.0937	0.126	0.343	0.193

Table I4: Staggered Diff-in-Diff - Weak Interbank, Cluster survey

Variables	(I) Access Finance (dummy)	(II) Bank Credit (dummy)	(III) Sales ln(USD)	(IV) Maturity ln(Months)
$Submarine_{ct}$	0.0437	-0.00197	-0.168	0.587**
	(0.0436)	(0.0338)	(0.881)	(0.214)
$Submarine \times Weak\ Intb_{ct}$	0.160***	0.0977***	3.821***	0.418*
	(0.0460)	(0.0256)	(0.922)	(0.238)
Country FE	Yes	Yes	Yes	No
Year FE	Yes	Yes	Yes	Yes
Obs.	25389	25222	24064	1139
Adj. R^2	0.0965	0.127	0.334	0.127
M.D.V.	0.638	0.211	12.11	3.008

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