

How abundant are reserves?
Evidence from the wholesale payment system

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Policy backdrop

- ◇ Monetary policy normalization
 - Balance sheet reduction

- ◇ Adequacy of reserve balances

- ◇ This paper approaches reserve ampleness through the lens of payment dynamics

Reserve balances and payments

- ◇ Prior to the Global Financial Crisis,
 - Reserves were low relative to payments
 - Banks relied on incoming payments to make payments
 - Strategic complementarities in payments

- ◇ Since then,
 - Central banks have expanded balance sheets (LSAPs, liquidity facilities)
 - Large increase in reserve balances in many jurisdictions

- ◇ Do strategic complementarities in payments still exist?

Outline

- ◇ Data
- ◇ Empirical results
- ◇ Robustness

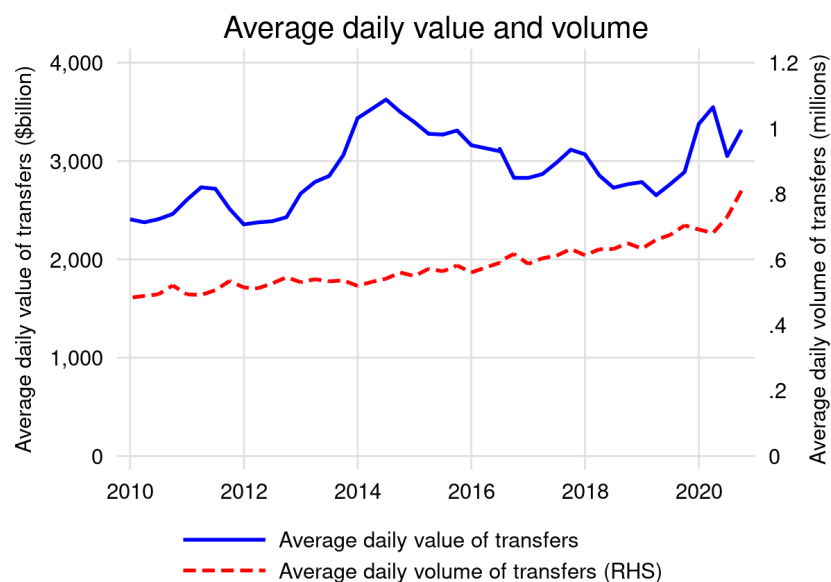
Data

1. Payment transactions

- ◇ Fedwire Funds Service
 - * Real time gross settlement (RTGS) system
 - * 21.5 hour day: 9:00 pm - 6:30 pm ET
 - * Daily volume (2020): ~ 700,000 transfers
 - * Daily value (2020): ~ \$3.3 trillion

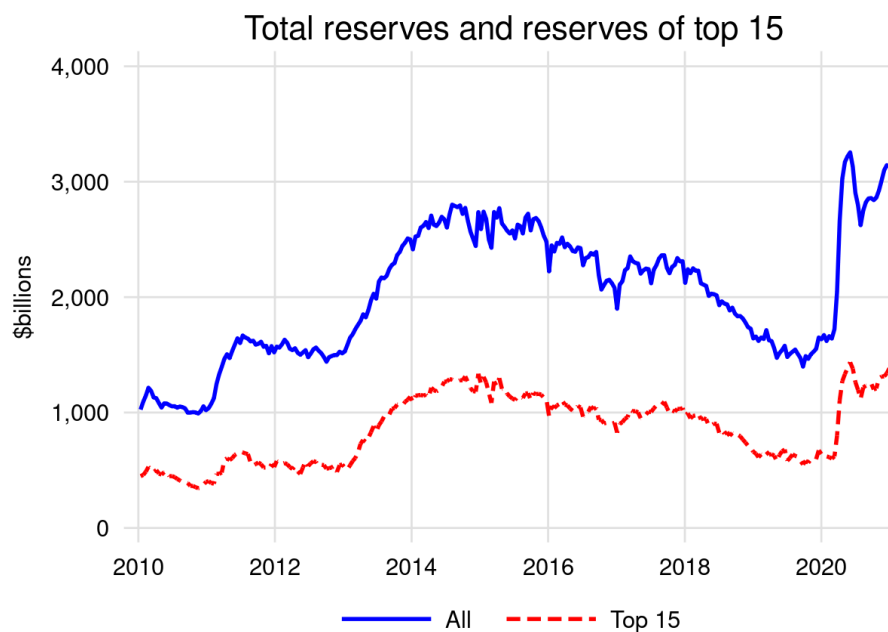
- ◇ Our sample:
 - * First 100 business days of 2020; 2010-2020
 - * Minute-by-minute

- * Banks - Excludes “special” accounts (ACH, CHIPS, CLS, TGA,...)
- * Largest top 100 accounts by average daily dollar value of payments
- * Dollar value (2020)
 - Top 100 captures 89% of dollar value (~\$3 tn per day)
 - Top 15 captures 76% of top 100 value



2. Reserve balances

- ◇ Internal Federal Reserve accounting records
- ◇ Top 15 accounts hold 40% of the reserves in the U.S. banking system

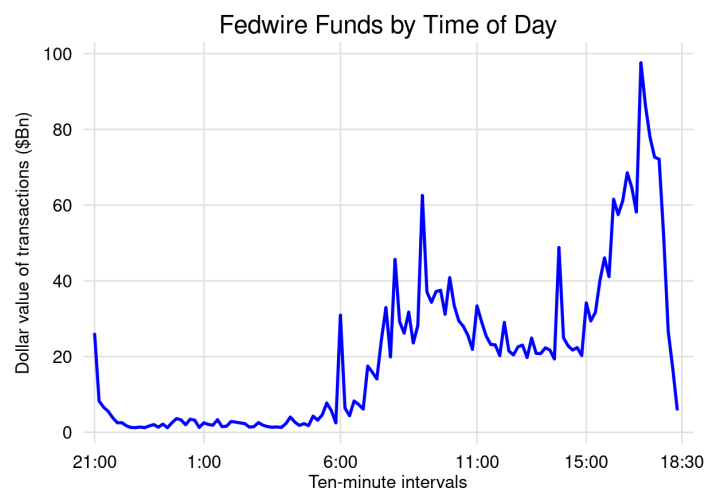


Strategic complementarity in payments

◇ Key relationship: $\text{Payments}_t = f(\text{Cumulative Receipts}_{t-s})$

◇ Distinctive data features

1. Intraday dynamics



2. Zero payments

Our model

- ◇ Baseline specification (Tobit model)

$$\log(1 + P_{imt}) = \beta_0 + \beta_1 \log\left(1 + \sum_{s=m-15}^{m-1} R_{ist}\right) + \gamma_i + \gamma_t + \gamma_m^p + u_{imt}$$

where

- P_{imt} total dollar value payments from bank i to its counterparties in minute m on day t
- $\sum_{s=m-15}^{m-1} R_{ist}$ bank i 's cumulative receipts during previous 15 minutes
- γ_i and γ_t are bank and date FEs
- $\gamma_m^p = \{\gamma_m^{open}, \gamma_m^{early}, \gamma_m^{afternoon}, \gamma_m^{eod}\}$ are period-of-day FEs
- u_{imt} is an error term

Standard errors clustered at the bank level

Main results

	log(1 + P_{imt})	
	Tobit (MLE)	
	(1)	(2)
	Coefficient	Marginal
log(1 + $\sum_{s=m-15}^{m-1} R_{ist}$)	0.575*** (0.179)	0.395
Clustering	Bank	
Bank FEs	Y	
Date FEs	Y	
Early dummy	Y	
EOD dummy	Y	
Afternoon dummies	Y	
Open dummy	Y	
N	1,935,000	
Left-censored	875,098	
Pseudo R^2	0.228	
Log-likelihood	-3,157,609.4	

Marginal effect. A 1% increase in the cumulative payments received by bank i in the previous 15 minutes translates into a 0.4% increase in the value of payments that bank i makes over the next minute.

Robustness

1. Bank, date, and period-of-the-day fixed effects

2. Control for balances

- Opening balances

- Past payments

3. Gauging strategic complementarities

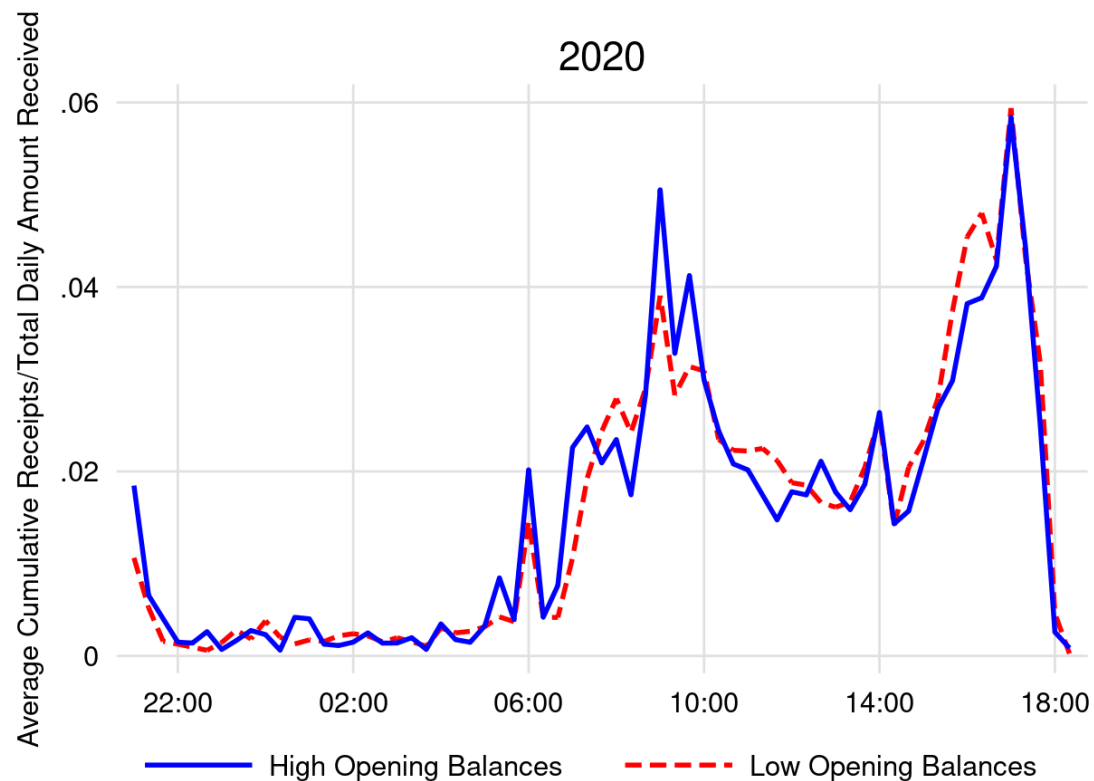
Complementarity is stronger when banking system reserves are lower

Robustness

	(1)	(2)	(8)	(9)
	$\log(1 + P_{imt})$	$\log(1 + P_{imt})$	$\log(1 + P_{imt})$	$\log(1 + P_{imt})$
$\log(1 + \sum_{s=m-15}^{m-1} R_{ist})$	0.575*** (0.179)	0.575*** (0.019)	2.891** (1.147)	3.131** (1.323)
$\log B_t$			1.474 (1.117)	
$\log B_t \times \log(1 + \sum_{s=m-15}^{m-1} R_{ist})$			-0.194* (0.105)	
$\log \text{Reserves}_t$				1.573 (1.228)
$\log \text{Reserves}_t \times \log(1 + \sum_{s=m-15}^{m-1} R_{ist})$				-0.207* (0.117)
Marginal effect of receipts	.395	.395	.395	.395
Clustering	Bank	Bank \times Day	Bank	Bank
Bank FEs	Y	Y	Y	Y
Date FEs	Y	Y	Y	Y
Early dummy	Y	Y	Y	Y
EOD dummy	Y	Y	Y	Y
Afternoon dummies	Y	Y	Y	Y
Open dummy	Y	Y	Y	Y
N	1,935,000	1,935,000	1,935,000	1,935,000
Left-censored	875,098	875,098	875,098	875,098
Pseudo R^2	0.228	0.228	0.228	0.228

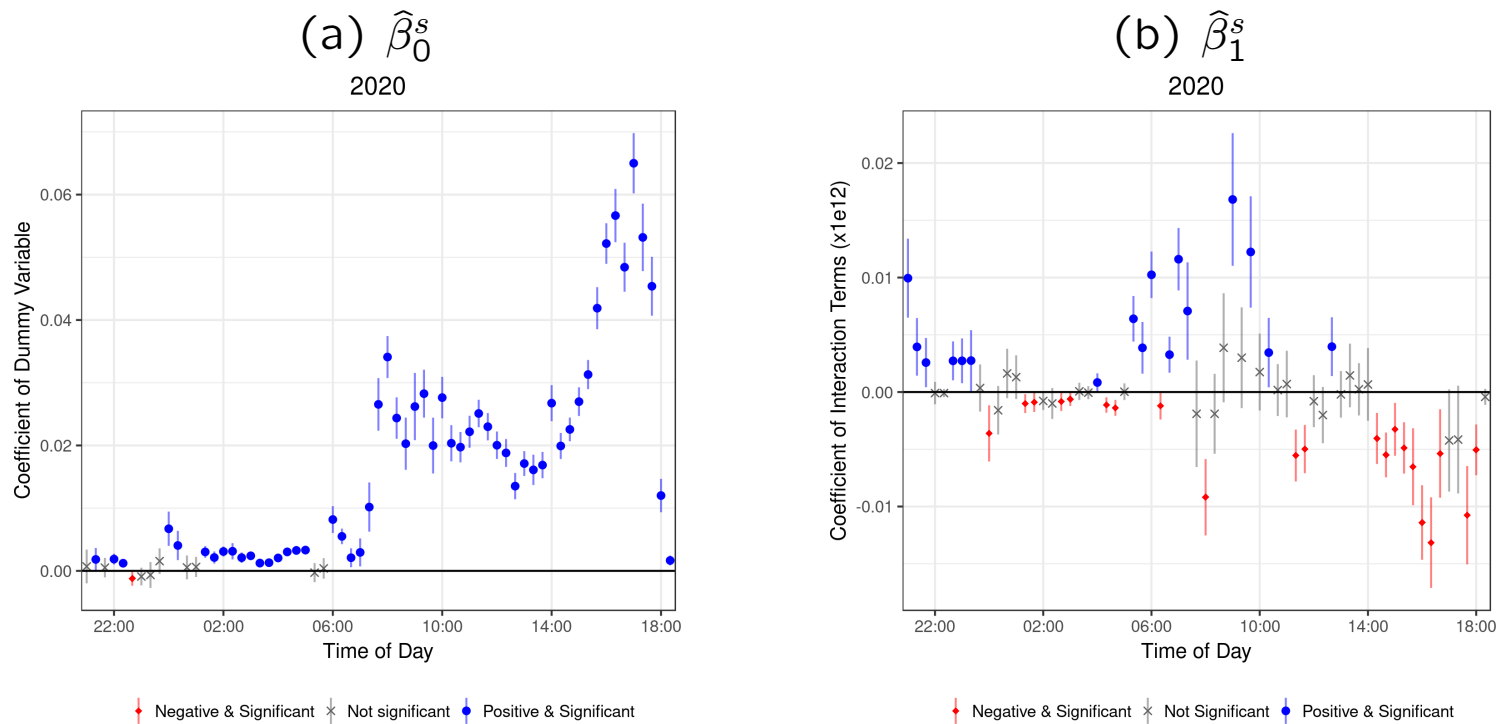
Values are log dollars. Sample is top 15 entities by average daily payment value in first 100 days of 2020.

Different intraday payments dynamics



Share of receipts by time of day

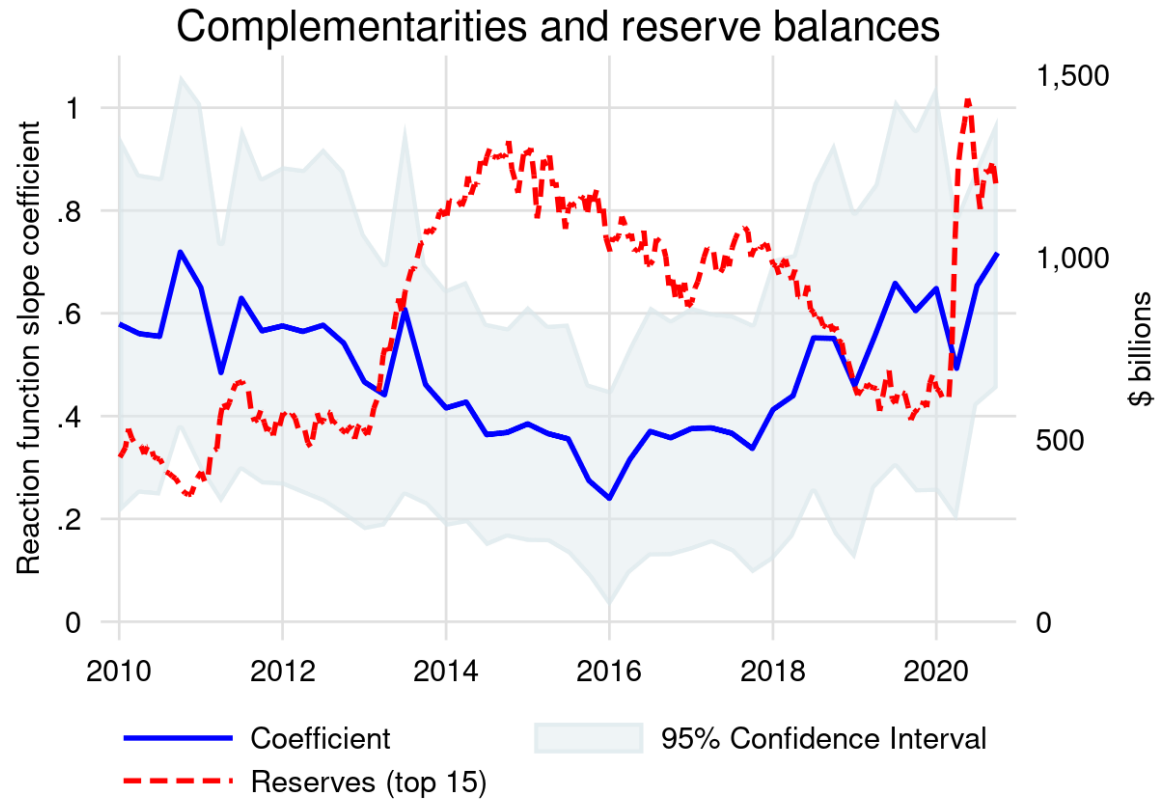
$$ShareReceipts_t^s = \beta_0^s + \beta_1^s B_t + u_t^s$$



On high reserve days, banks receive a higher share of receipts in the morning

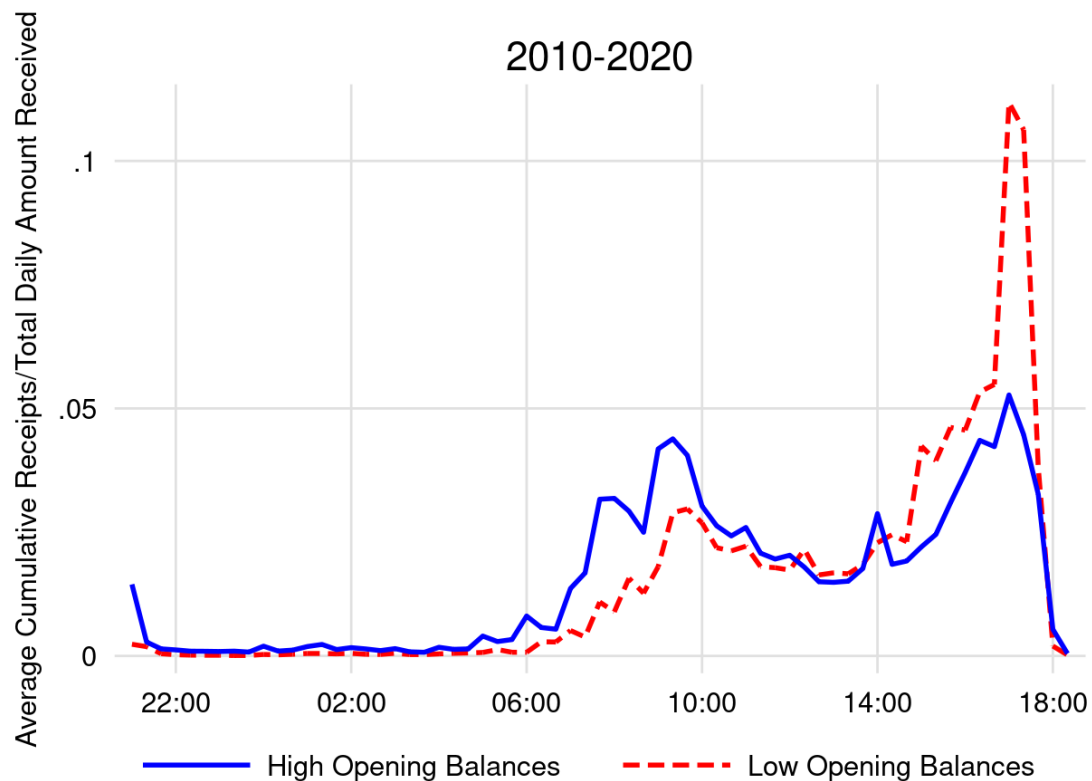
A feature of 2020?

Complementarities in payments



Coordination is higher when reserves are lower

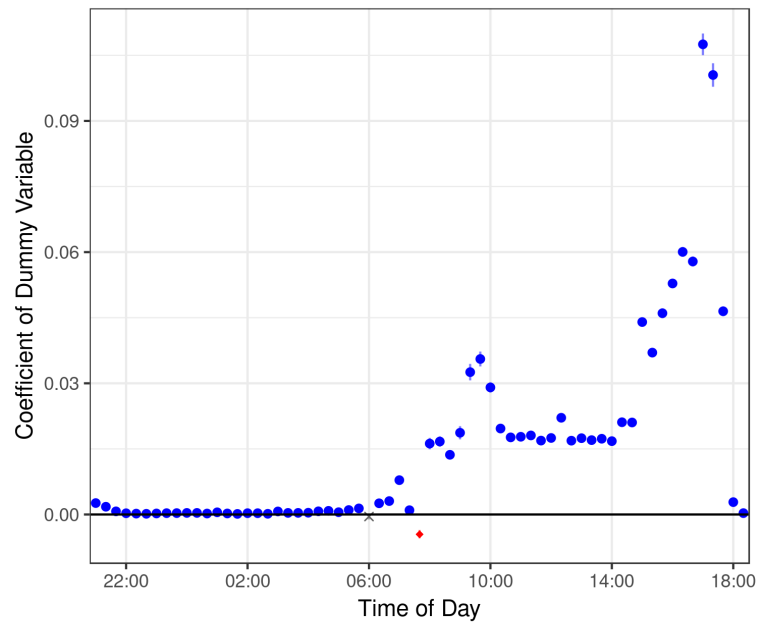
Share of payments by time of day



Reserves and timing of intraday payments

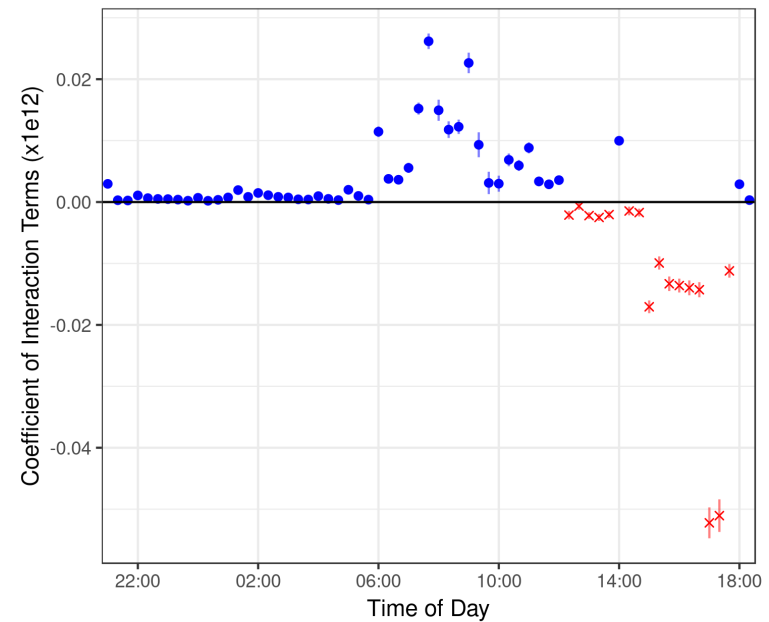
$$ShareReceipts_t^s = \beta_0^s + \beta_1^s B_t + u_t^s$$

(a) $\hat{\beta}_0^s$
2010-2020



◆ Negative & Significant ✖ Not significant ● Positive & Significant

(b) $\hat{\beta}_1^s$
2010-2020



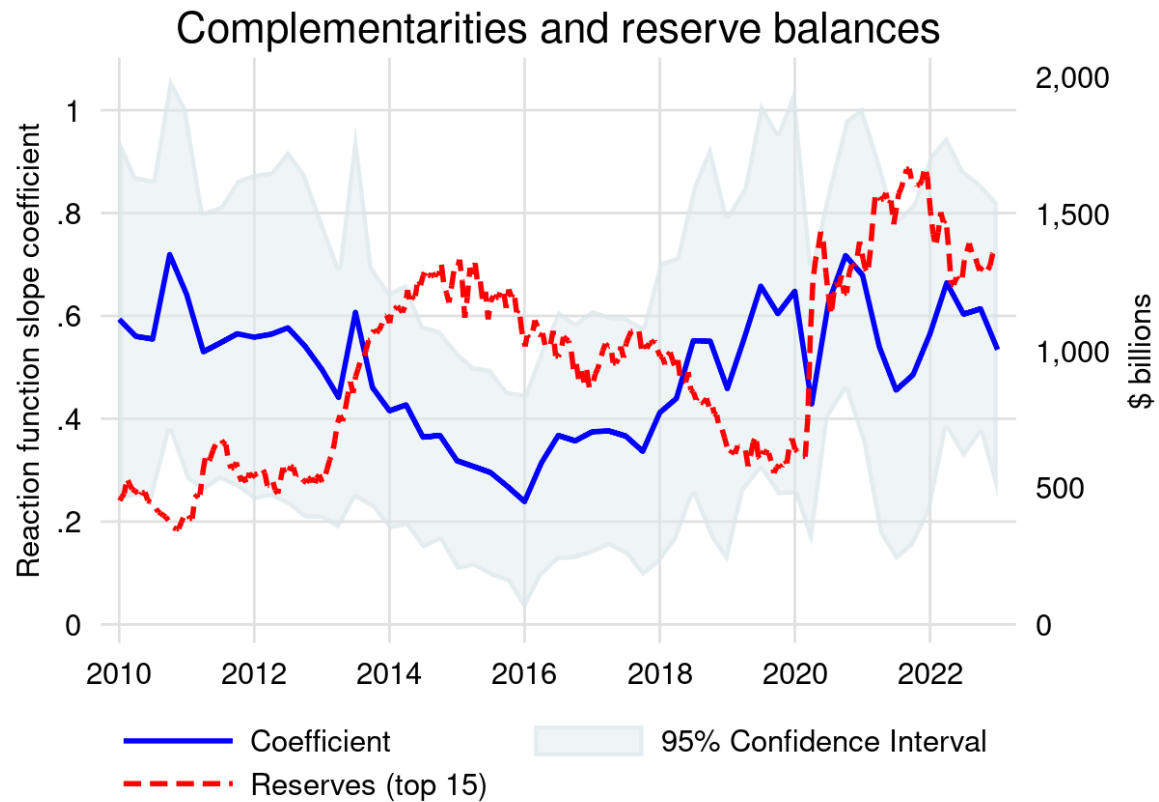
◆ Negative & Significant ● Positive & Significant

Concluding remarks

- ◇ Shed light on "ampleness" of reserves through revealed actions in payments
 - A 1% increase in the payments a bank receives in previous 15 minutes translates into a 0.4% increase in the payments it makes next minute
- ◇ This effect persists even in era of high reserve balances
- ◇ On days with low reserve balances,
 - Stronger effect
 - Banks receive a higher fraction of their receipts in the afternoon

Appendix

Complementarities in payments



Coordination is higher when reserves are lower

Robustness - 2020

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$\log(1 + P_{imt})$	$\log(1 + P_{imt})$	$\log(1 + P_{imt})$	$\log(1 + P_{imt})$	$\log(1 + P_{imt})$	$\log(1 + P_{imt})$	$\log(1 + \sum_{s=m}^{m+4} P_{ist})$	$\log(1 + P_{imt})$	$\log(1 + P_{imt})$
$\log(1 + \sum_{s=m-15}^{m-1} R_{ist})$	0.575*** (0.179)	0.575*** (0.019)	0.575*** (0.179)	0.302*** (0.117)	0.340*** (0.086)		0.519*** (0.145)	2.891** (1.147)	3.131** (1.323)
$\log(1 + \sum_{s=m-30}^{m-1} R_{ist})$						0.842*** (0.306)			
$\log B_{it}$			0.089* (0.050)						
$\log(1 + \sum_{s=1}^{m-16} P_{ist})$				0.899*** (0.121)					
$\log(1 + P_{im-1t})$					0.681*** (0.065)				
$\log B_t$								1.474 (1.117)	
$\log B_t \times \log(1 + \sum_{s=m-15}^{m-1} R_{ist})$								-0.194* (0.105)	
$\log \text{Reserves}_t$									1.573 (1.228)
$\log \text{Reserves}_t \times \log(1 + \sum_{s=m-15}^{m-1} R_{ist})$									-0.207* (0.117)
Marginal effect of receipts	.395	.395	.395	.189	.257	.57	.469	.395	.395
Clustering	Bank	Bank × Day	Bank	Bank	Bank	Bank	Bank	Bank	Bank
Bank FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Date FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Early dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y
EOD dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y
Afternoon dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y
Open dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	1,935,000	1,935,000	1,935,000	1,935,000	1,935,000	1,935,000	1,935,000	1,935,000	1,935,000
Left-censored	875,098	875,098	875,098	875,098	875,098	875,098	656,455	875,098	875,098
Pseudo R^2	0.228	0.228	0.228	0.258	0.277	0.230	0.214	0.228	0.228

Values are log dollars. Sample is top 15 entities by average daily payment value in first 100 days of 2020.

Robustness - 2010-20

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$\log(1 + P_{imt})$	$\log(1 + P_{imt})$	$\log(1 + P_{imt})$	$\log(1 + P_{imt})$	$\log(1 + P_{imt})$	$\log(1 + P_{imt})$	$\log(1 + \sum_{s=m}^{m+4} P_{ist})$	$\log(1 + P_{imt})$	$\log(1 + P_{imt})$
$\log(1 + \sum_{s=m-15}^{m-1} R_{ist})$	0.490*** (0.115)	0.490*** (0.003)	0.490*** (0.115)	0.323*** (0.067)	0.295*** (0.046)		0.476*** (0.074)	3.865** (1.635)	4.290** (2.051)
$\log(1 + \sum_{s=m-30}^{m-1} R_{ist})$						0.640*** (0.196)			
$\log B_{it}$			-0.045 (0.112)						
$\log(1 + \sum_{s=1}^{m-16} P_{ist})$				0.804*** (0.107)					
$\log(1 + P_{im-1t})$					0.732*** (0.080)				
$\log B_t$								2.367** (1.156)	
$\log B_t \times \log(1 + \sum_{s=m-15}^{m-1} R_{ist})$								-0.284** (0.139)	
$\log \text{Reserves}_t$									2.584* (1.396)
$\log \text{Reserves}_t \times \log(1 + \sum_{s=m-15}^{m-1} R_{ist})$									-0.310* (0.169)
Marginal effect of receipts	.234	.234	.234	.128	.17	.29	.366	.232	.233
Clustering	Bank	Bank × Day	Bank	Bank	Bank	Bank	Bank	Bank	Bank
Bank FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Date FEs	N	N	N	N	N	N	N	N	N
Early dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y
EOD dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y
Afternoon dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y
Open dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y
Day-of-week FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month-of-year FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month-end dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y
Mid-month dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarter-year FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	53,270,550	53,270,550	53,270,550	53,270,550	53,270,550	53,270,550	53,270,550	53,270,550	53,270,550
Left-censored	28,541,241	28,541,241	28,541,241	28,541,241	28,541,241	28,541,241	22,790,543	28,541,241	28,541,241
Pseudo R^2	0.263	0.263	0.263	0.288	0.316	0.264	0.250	0.263	0.263

Values are log dollars. Sample is top 15 entities by average daily payment value in 2010-2020.

Placebo

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$\log(1 + R_{imt})$	$\log(1 + R_{imt})$	$\log(1 + R_{imt})$	$\log(1 + R_{imt})$	$\log(1 + R_{imt})$	$\log(1 + R_{imt})$	$\log(1 + \sum_{s=m}^{m+4} R_{ist})$	$\log(1 + R_{imt})$	$\log(1 + R_{imt})$
$\log(1 + \sum_{s=m-15}^{m-1} R_{ist})$	0.545*** (0.066)	0.545*** (0.007)	0.545*** (0.066)	0.484*** (0.059)	0.507*** (0.050)		0.466*** (0.019)	0.556 (0.534)	0.527 (0.648)
$\log(1 + \sum_{s=m-30}^{m-1} R_{ist})$						0.653*** (0.095)			
$\log B_{it}$			0.054 (0.069)						
$\log(1 + \sum_{s=1}^{m-16} P_{ist})$				0.119*** (0.026)					
$\log(1 + P_{im-1t})$					0.138*** (0.031)				
$\log B_t$								0.170 (0.471)	
$\log B_t \times \log(1 + \sum_{s=m-15}^{m-1} R_{ist})$								-0.001 (0.045)	
$\log \text{Reserves}_t$									0.162 (0.541)
$\log \text{Reserves}_t \times \log(1 + \sum_{s=m-15}^{m-1} R_{ist})$									0.001 (0.053)
Marginal effect of receipts	.481	.481	.481	.427	.451	.574	.465	.481	.481
Clustering	Bank	Bank × Day	Bank	Bank	Bank	Bank	Bank	Bank	Bank
Bank FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Date FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Early dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y
EOD dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y
Afternoon dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y
Open dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	1,935,000	1,935,000	1,935,000	1,935,000	1,935,000	1,935,000	1,935,000	1,935,000	1,935,000
Left-censored	640,115	640,115	640,115	640,115	640,115	640,115	323,739	640,115	640,115
Pseudo R^2	0.215	0.215	0.215	0.216	0.217	0.213	0.234	0.215	0.215

Values are log dollars. Sample is top 15 entities by average daily payment value in first 100 days of 2020.

Bank payments and receipts: OLS vs. Tobit

	$\log(1 + P_{imt})$			
	Linear (OLS)		Tobit (MLE)	
	(1)	(2)	(3)	(4)
	$y \geq 0$	$y > 0$	Coefficient	Marginal
$\log(1 + \sum_{s=m-15}^{m-1} R_{ist})$	0.040 (0.083)	0.119* (0.062)	0.575*** (0.179)	0.395
Clustering	Bank	Bank	Bank	
Bank FEs	Y	Y	Y	
Date FEs	Y	Y	Y	
Early dummy	Y	Y	Y	
EOD dummy	Y	Y	Y	
Afternoon dummies	Y	Y	Y	
Open dummy	Y	Y	Y	
N	1,935,000	1,059,902	1,935,000	
Left-censored			875,098	
R^2	0.597	0.355		
Pseudo R^2			0.228	
Log-likelihood			-3,157,609.4	