Monetary Policy Operations:
Theory, Evidence, and Tools for Quantitative Analysis

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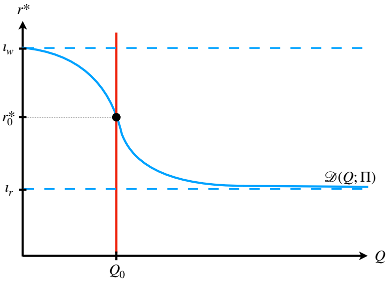
Operating frameworks to implement a FFR target

Corridor system

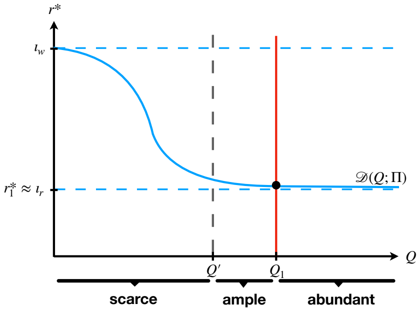
- pre-GFC
- *scarce* reserves
- Fed manages quantity of reserves



- requires *local* demand estimates

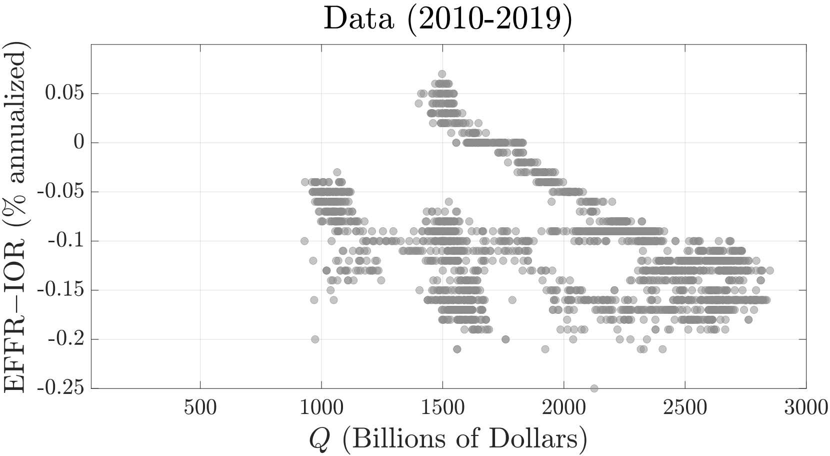
Floor system

- post-GFC
- *abundant* reserves
- Fed manages administered rates



- requires *global* demand estimates

Can you identify a "demand for reserves"?



- LCR phased in between Jan 2015 and Jan 2017
- SLR compliance since Jan 2018
- Changes in administered rates

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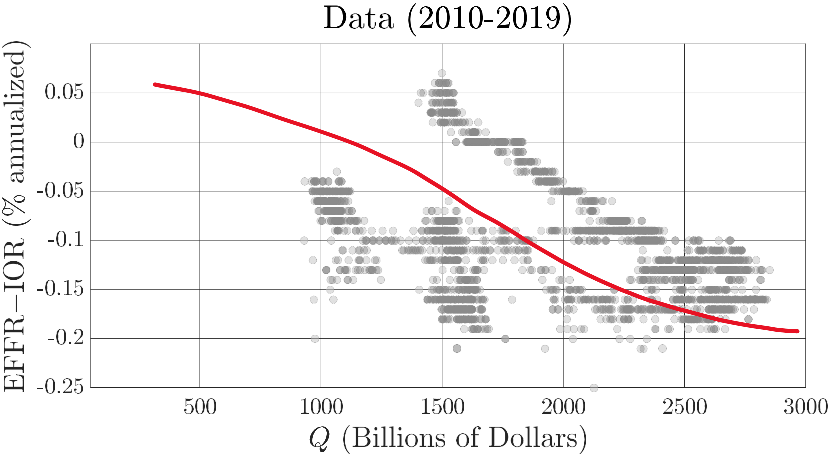

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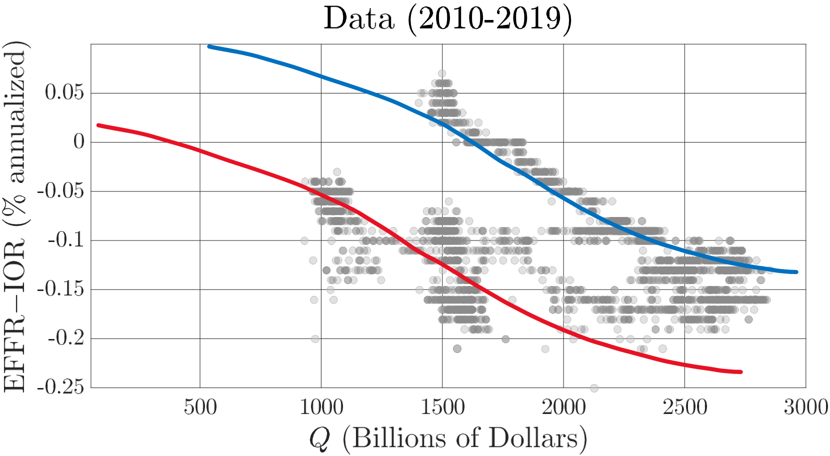

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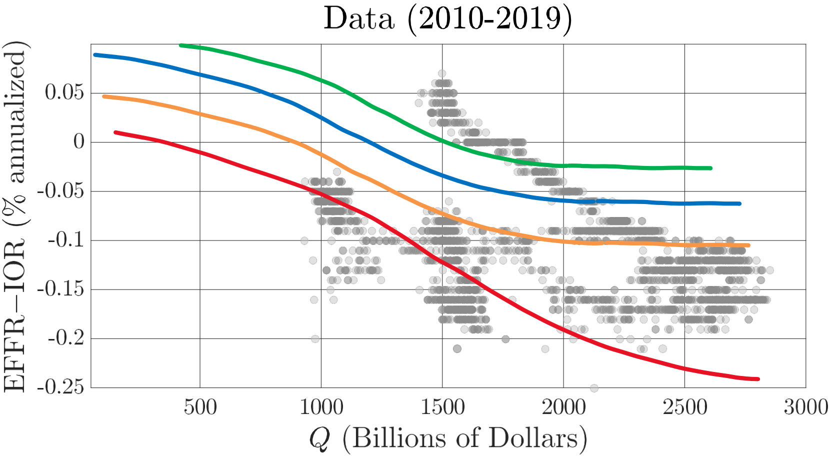


- LCR phased in between Jan 2015 and Jan 2017
- SLR compliance since Jan 2018
- Changes in administered rates

Our approach

Use quantitative theory to deliver a structural estimate of the aggregate demand for reserves in the United States

Discipline — Parameters of the theory are calibrated to fit:

- "local" slope and position of the empirical reserve demand
- key cross-sectional bank-level fed-funds statistics (participation rates in trade volume, intermediation)

Questions

answers

The fed funds market has operated with very large supply of reserves for over a decade...

- What does the reserve demand look like for lower quantities?

The Fed has announced it intends to continue operating a floor system with "ample reserves, in which active management of the supply of reserves is not required"

- What quantity of reserves is "ample enough"?

What we do

literature

- Document new micro and marketwide facts
- Extend the prototypical structural model of the federal funds market (Afonso and Lagos (2015)) by incorporating bank-level heterogeneity
- Show the heterogeneous-bank OTC theory can match key facts
- Use the quantitative theory to:
  - estimate the aggregate demand for reserves in the United States
  - develop "navigational tools" for monetary policy implementation

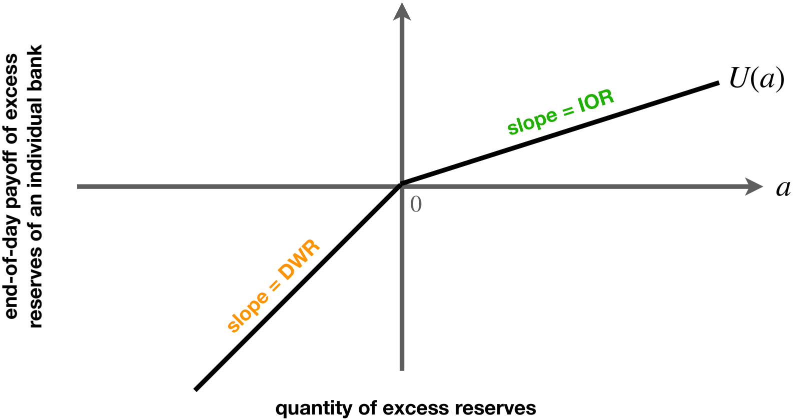
Theory

Model

- Continuous-time *trading day*, $[0, T] \equiv \mathbb{T}$
- Unit measure of heterogeneous *banks*; n_i of type $i \in \mathbb{N}$
- Banks hold *reserve balances*, $a \in \mathbb{R}$, with CDF $F_t^i(\cdot)$, for $(i, t) \in \mathbb{N} \times \mathbb{T}$; $\{F_0^i(\cdot)\}_{i \in \mathbb{N}}$, given; $Q \equiv \int a dF_0(a)$, where $F_t(a) = \sum_{i \in \mathbb{N}} n_i F_t^i(a)$
- End-of-day payoff from holding reserve balance $a \in \mathbb{R}$: $\{U_i(a)\}_{i \in \mathbb{N}}$
- Banks can borrow and lend reserves in an OTC marketstructure:
  - trade opportunities: bilateral and random; Poisson rates $\{\beta_i\}_{i \in \mathbb{N}}$
  - loan size and repayment: Nash bargaining, with weights $\{\theta_{ij}\}_{i,j \in \mathbb{N}}$
- Banks are subject to idiosyncratic *payment shocks*:
  - frequency: Poisson rates $\{\lambda_i\}_{i \in \mathbb{N}}$
  - size distribution: $\{G_{ij}\}_{i,j \in \mathbb{N}}$

☞ type $i \in \mathbb{N}$ is defined by the primitives $(n_i, \beta_i, \lambda_i, \{\theta_{ij}, G_{ij}\}_{j \in \mathbb{N}}, u_i, U_i)$

Intuition: shadow interest rates



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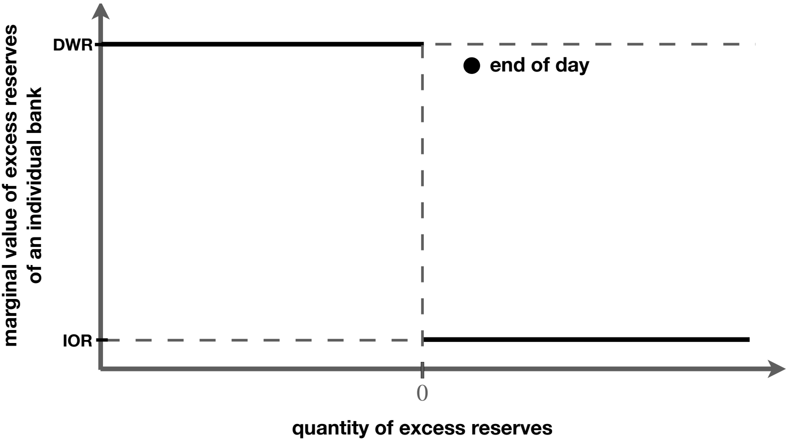

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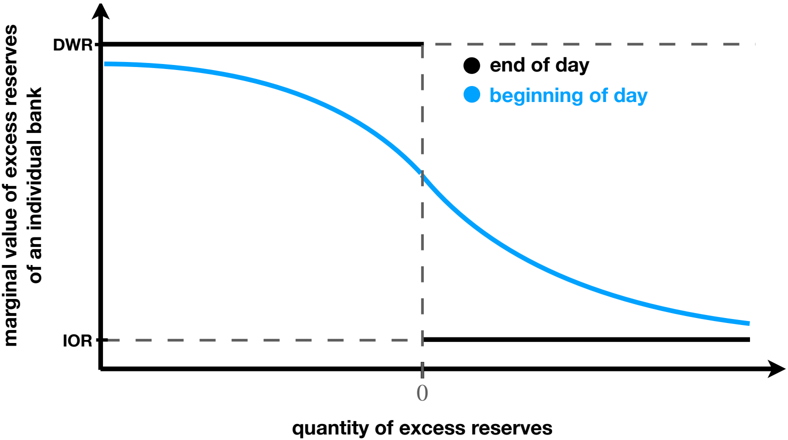

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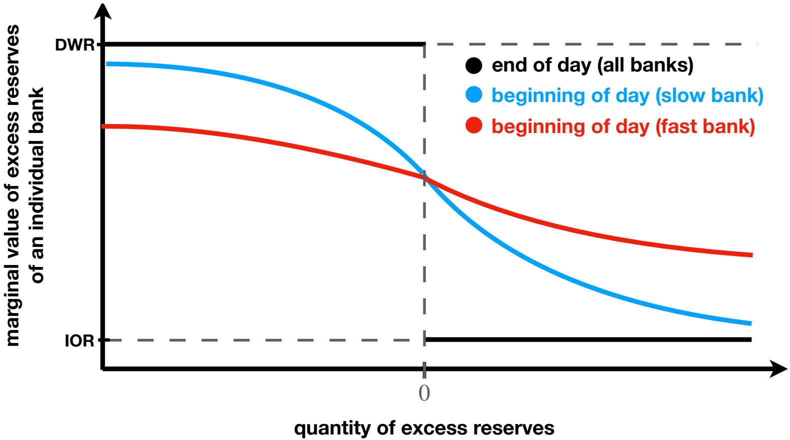


Evidence

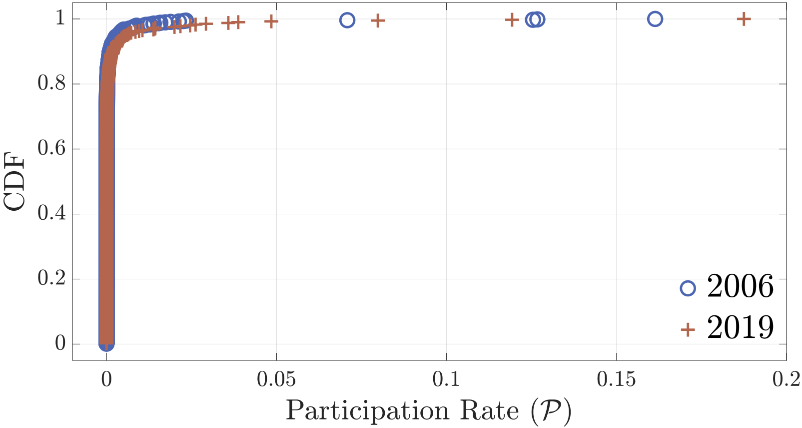
Data

sources

Descriptive statistics (later used for calibration):

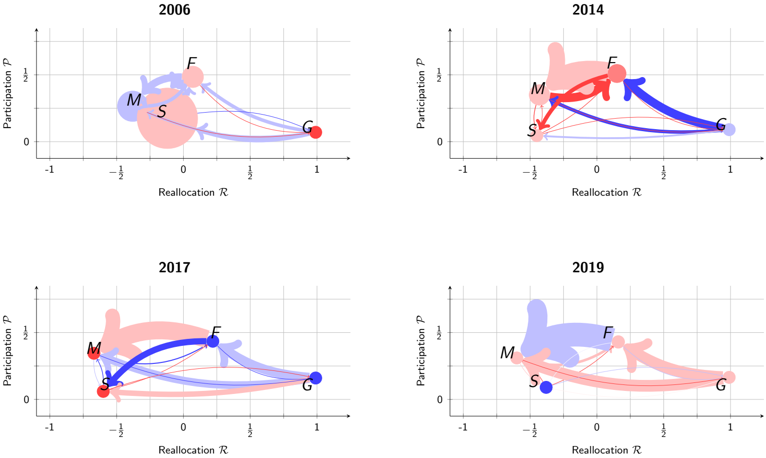
1. Fed funds trading activity
2. Payments
3. Beginning-of-day distribution of reserves
4. *Liquidity effect* (local slope of reserve demand)
5. Reserve-draining shocks (variation in supply)

Use $\mathcal{P}_{nd} \equiv \frac{v^e_{nd}+v^r_{nd}}{2v_d}$ to define four *types*: $\{F, M, S, G\}$



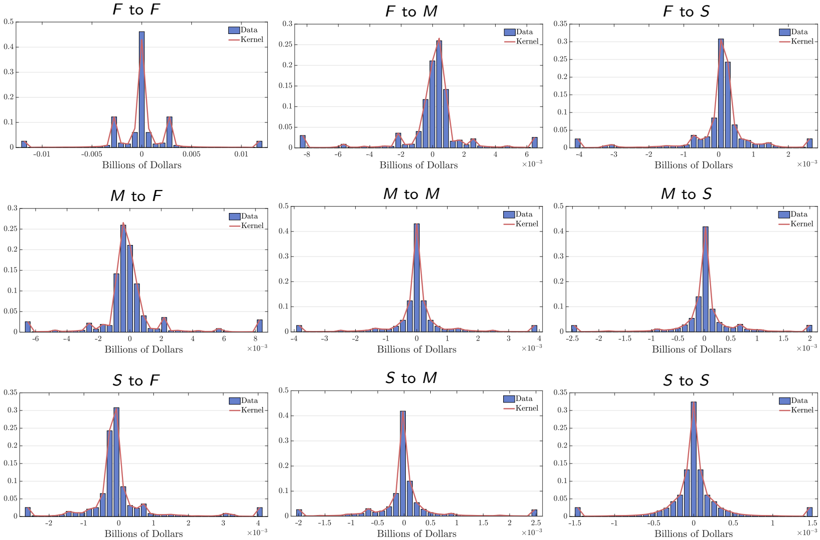
- "F": top 4 banks
- "M": banks with $\mathcal{P}_n \geq 0.01$ (other than top 4)
- "S": banks with $\mathcal{P}_n < 0.01$
- "G": Government Sponsored Enterprises

Fed funds network: $\mathcal{P}_{nd} \equiv \frac{v^e_{nd}+v^r_{nd}}{2v_d}$ and $\mathcal{R}_{nd} \equiv \frac{v^e_{nd}-v^r_{nd}}{v^e_{nd}+v^r_{nd}}$



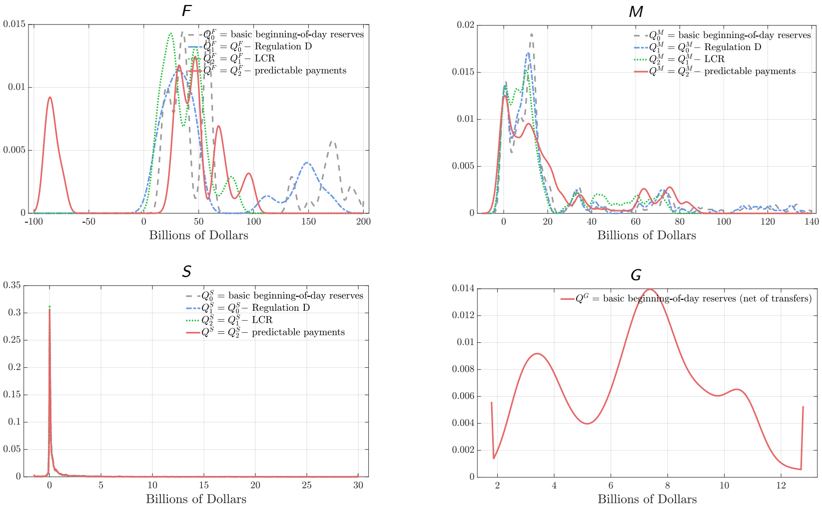
Size distributions of payment shocks (2019)

year 2006



Beginning-of-day distributions of reserves (2019)

other years



Liquidity effect: estimation

identification validation

We estimate:

$$s_t - s_{t-1} = \gamma_0 + \gamma(Q_t - Q_{t-1}) + \varepsilon_t$$

- s_t : EFFR-IOR spread on day t (in bps)
- Q_t : total reserves at the end of day t (in \$bn)
- Sample period: 2019/05/02–2019/09/13 (daily)
  - Identifying assumption: Fed was not actively managing quantity of reserves at daily frequency during this period
  - Constant DWR-ONRRP and IOR-ONRRP spreads (75 bps and 10 bps, resp., throughout the sample)
  - Same period we will use for our baseline calibration

The estimate is $\gamma = -0.0119$ (significant at the 1% level), with 95% confidence interval $[-0.0187, -0.0052]$

Calibration

Parameter	Target	Moment	
		Data	Model
$n_F = 0.010$	proportion of financial institutions of type F	4/412	0.010
$n_M = 0.044$	proportion of financial institutions of type M	18/412	0.044
$n_S = 0.920$	proportion of financial institutions of type S	379/412	0.920
$n_G = 0.026$	proportion of financial institutions of type G	11/412	0.026
$\lambda_F = 0.951$	bank-level share of unexpected payments per second for type F	0.951	0.951
$\lambda_M = 0.257$	bank-level share of unexpected payments per second for type M	0.257	0.257
$\lambda_S = 0.011$	bank-level share of unexpected payments per second for type S	0.011	0.011
$\lambda_G = 0$	bank-level share of unexpected payments per second for type G	0	0
$\iota_w = 0.0300/360$	DWR (3.00% per annum, primary credit)	0.0300/360	0.0300/360
$\iota_r = 0.0235/360$	IOR (2.35% per annum)	0.0235/360	0.0235/360
$\iota_o = 0.0225/360$	ONRRP (2.25% per annum)	0.0225/360	0.0225/360
$\iota_\ell = 0.00049/360$	average value-weighted fed funds rate	0.0239/360	0.0239/360
$\iota_s = 0.00758/360$	estimated liquidity effect for 2019 (bps per $1 bn decrease in reserves)	$\in [-0.019, -0.005]$	-0.0073
$\underline{\theta} = 1/20$	conditional (below the IOR) average value-weighted fed funds rate	0.0229/360	0.0231/360
$\beta_F = 0.0300$	number of loans of financial institutions of type F relative to average	24	25
$\beta_M = 0.0024$	participation rate of financial institutions of type M (i.e., $\mathcal{P}_M$)	0.31	0.27
$\beta_S = 0.0007$	participation rate of financial institutions of type S (i.e., $\mathcal{P}_S$)	0.09	0.08
$\beta_G = 0.0036$	participation rate of financial institutions of type G (i.e., $\mathcal{P}_G$)	0.17	0.14
$\kappa_F = 0.039e\text{-}3$	reallocation index of financial institutions of type F (i.e., $\mathcal{R}_F$)	0.16	0.13
$\kappa_M = 0$	reallocation index of financial institutions of type M (i.e., $\mathcal{R}_M$)	-0.61	-0.64
$\kappa_S = 0.003e\text{-}3$	reallocation index of financial institutions of type S (i.e., $\mathcal{R}_S$)	-0.38	-0.37
$\kappa_G = 1.25e\text{-}3$	reallocation index of financial institutions of type G (i.e., $\mathcal{P}_G$)	1	1

ω rule liquidity effect

Validation

Model fit

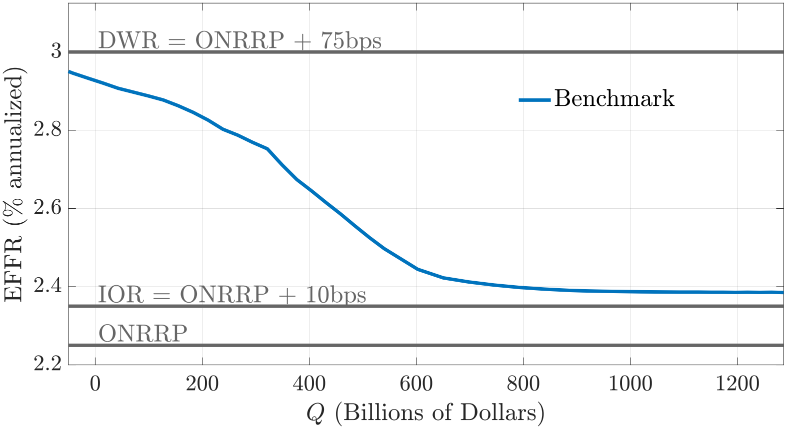
Good fit of prices and quantities *not* targeted in the calibration:

1. Distribution of loan rates
2. Conditional distribution of loan rates in excess of DWR
3. Bid-ask spread by bank type
4. Distributions of loan rates between pairs of bank types
5. Fed funds trading network

Aggregate Demand for Reserves

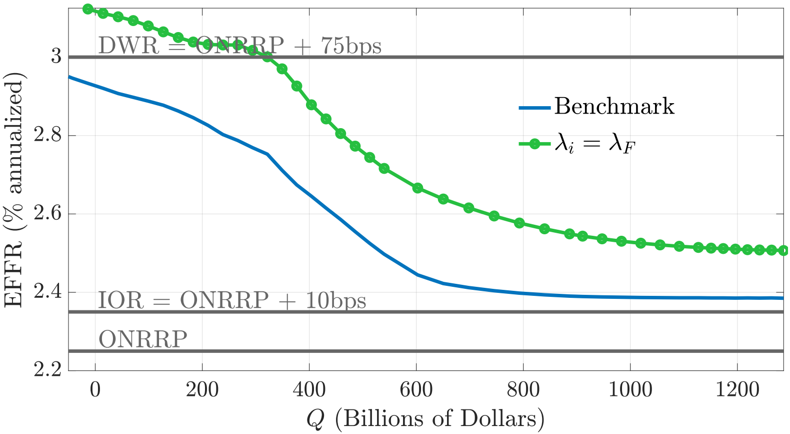
(Theory)

Aggregate demand for reserves in the theory



- Baseline rates calibrated to: 2019/06/06–2019/07/31; ONRRP = 2.25%; IOR = 2.35%; DWR = 3.0%

Counterfactual: higher frequency of payment shocks



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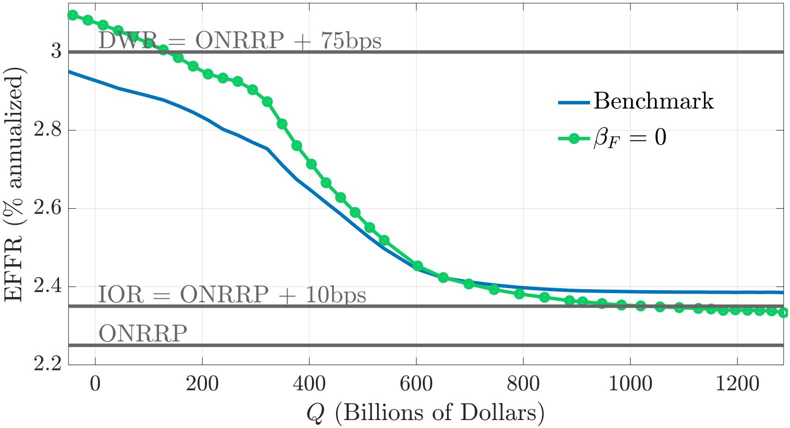
Counterfactual: F banks do not participate



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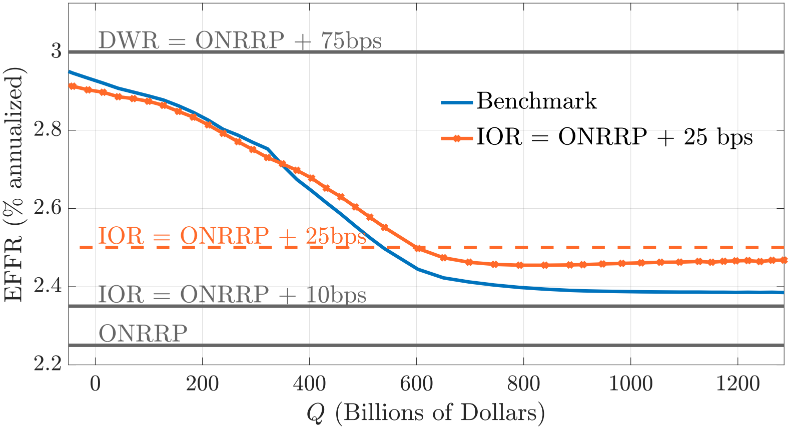
Counterfactual: IOR-ONRRP spread



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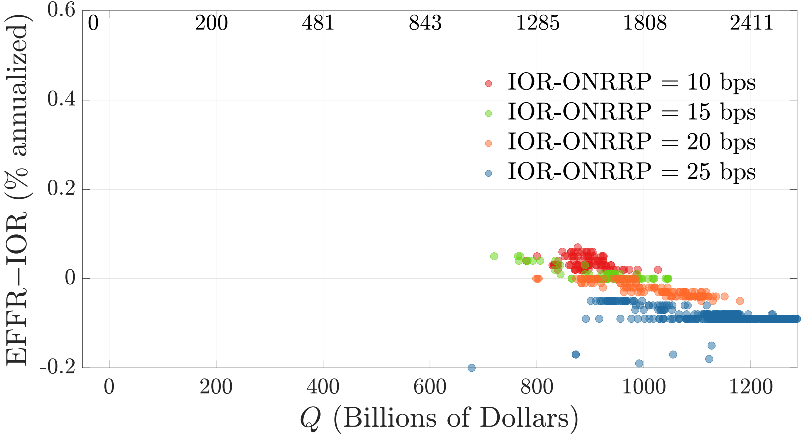
Aggregate Demand for Reserves

(Estimation)

Quantitative-theoretic estimation

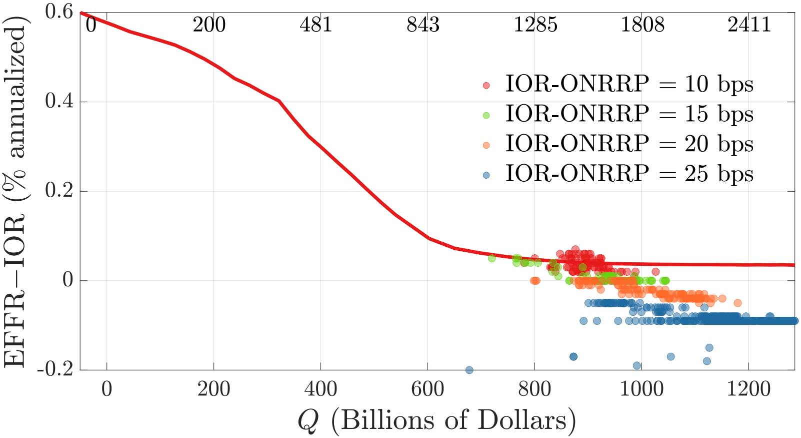
with 2023



- Sample 2017/01/20–2019/09/13 split by IOR-ONRRP regime

Quantitative-theoretic estimation

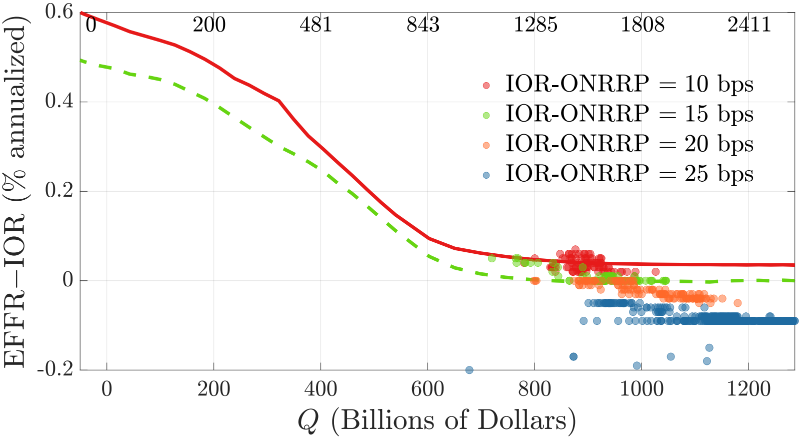
with 2023



- Sample 2017/01/20–2019/09/13 split by IOR-ONRRP regime
- ADR implied by the theory (baseline calibration, but with administered rates to match the subsample)

Quantitative-theoretic estimation

with 2023



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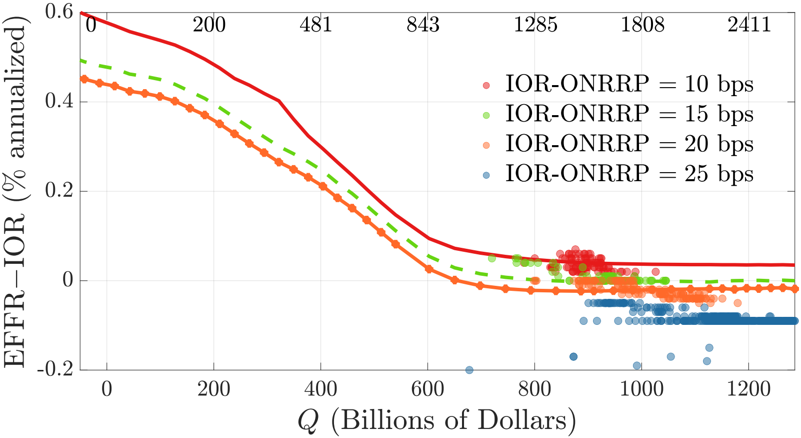

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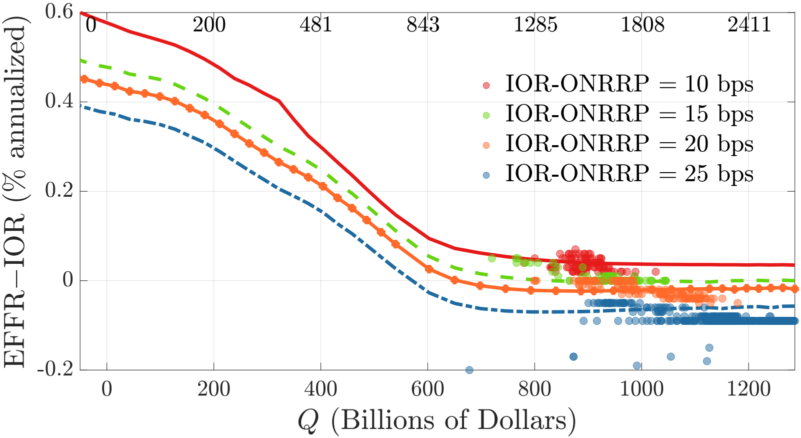

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Our Demand Estimation

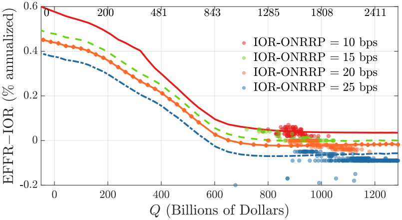
vs.

others

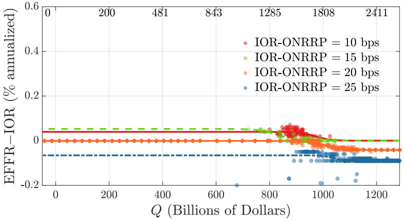
Quantitative-theoretic estimation vs. NLS fit

intro

Theoretical demand under baseline calibration



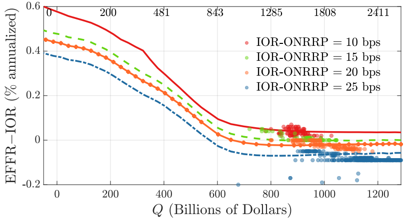
NLS fit of $s_t = D(Q_t) \equiv \underline{s} + \frac{\bar{s}-\underline{s}}{1+e^{(Q_t-Q_0)\xi}}$



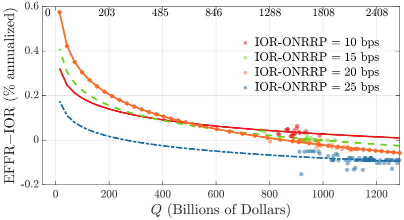
- Sample period: 2017/01/20–2019/09/13 split by IOR-ONRRP regime

Quantitative-theoretic estimation vs. LS-VJ OLS fit

Theoretical demand under baseline calibration



OLS fit of $s_t = D(Q_t) \equiv a + b\ln(Q_t) + c\ln(D_t)$



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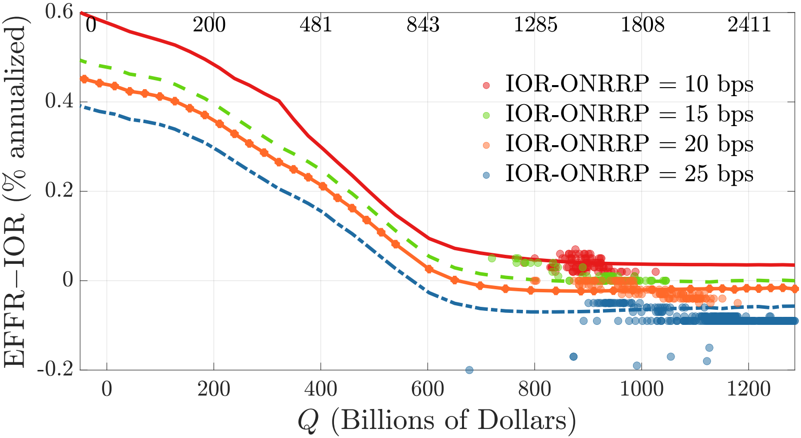
Quantitative-theoretic estimation



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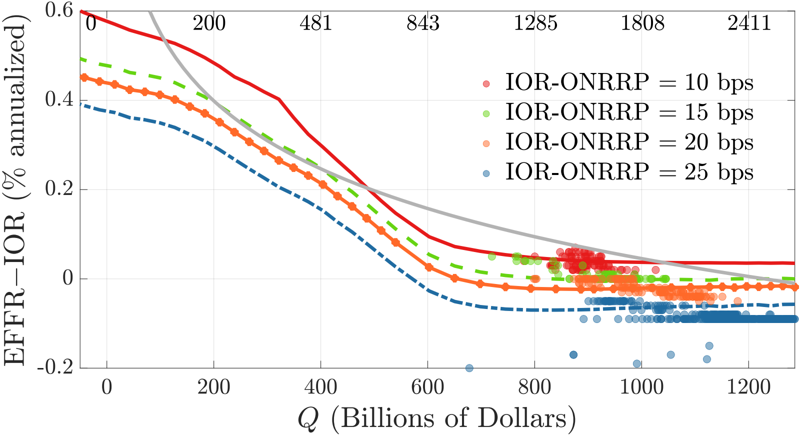
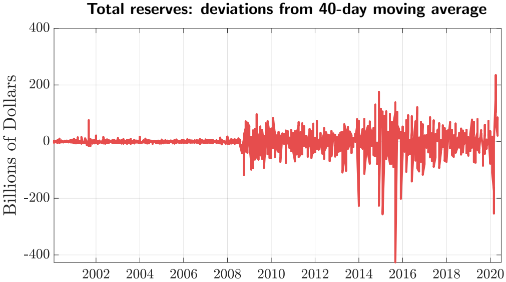


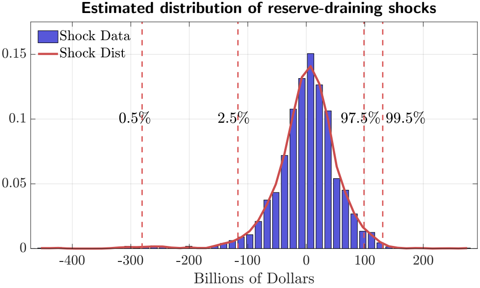
- Sample 2017/01/20–2019/09/13 split by IOR-ONRRP regime
- ADR implied by the theory (baseline calibration, but with administered rates to match the subsample)
- LS-VJ fit (2010-2019 sample, with demand deposits as control)

Monetary Confidence Bands

(MCB)

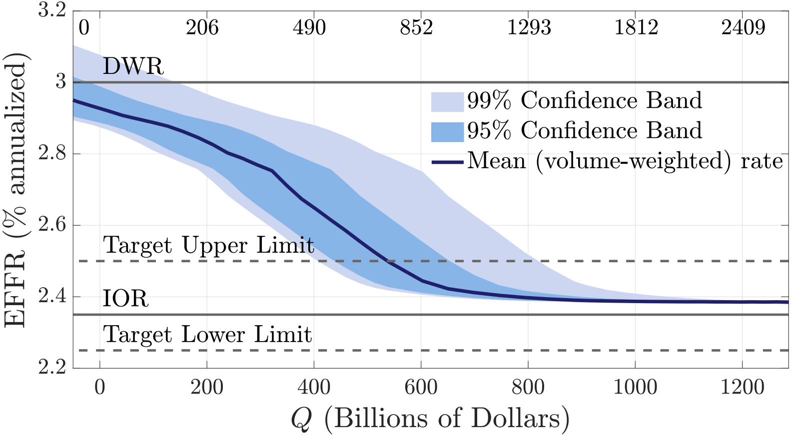
Variation in supply: reserve-draining shocks





Monetary Confidence Bands

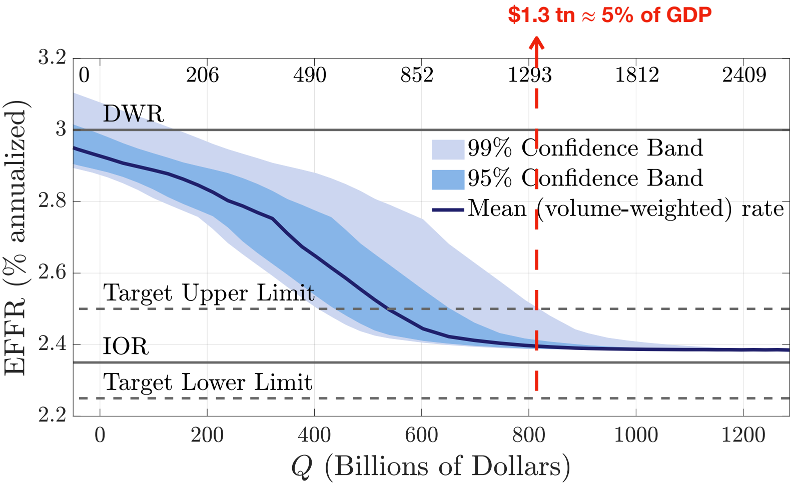
year 2023



- Baseline calibration. Administered and target rates as in 2019/06/06–2019/07/31: ONRRP = TRL = 2.25%; IOR = 2.35%; TRU = 2.50%; DWR = 3.0%

What quantity of reserves is “ample enough”?

year 2023



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Conclusion

Questions

- What quantity of reserves is “ample enough”?

- What does the reserve demand in the United States look like?

Questions + Answers

- What quantity of reserves is “ample enough”?

  \$1.3 tn

- What does the reserve demand in the United States look like?

Questions + Answers

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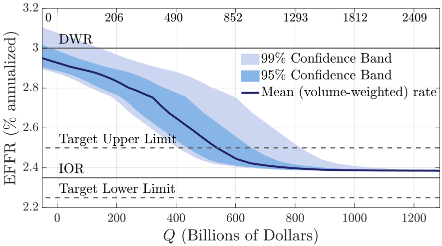
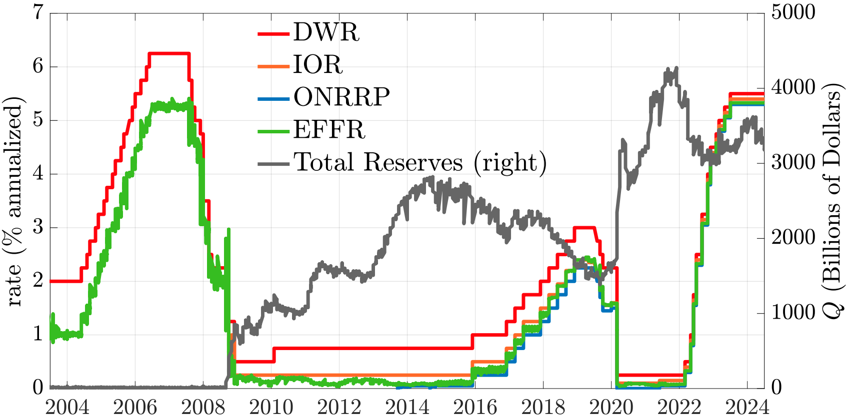


scan to find the paper

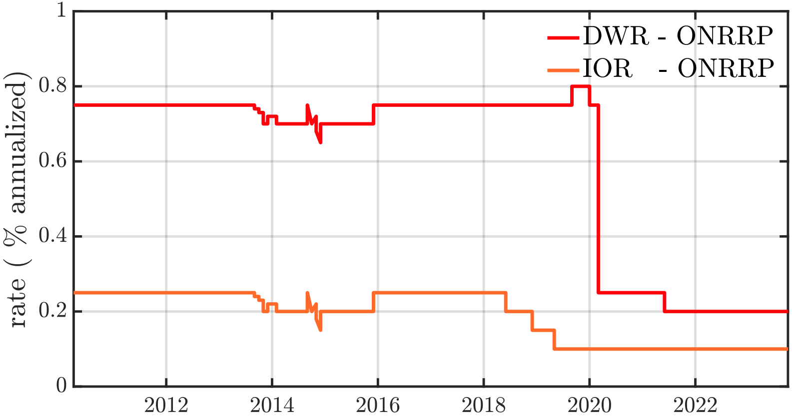
Appendix

Total Reserves, Administered Rates, EFFR

Reserves, administered rates, and EFFR



Administered spreads: DWR-ONRRP, IOR-ONRRP



Micro Data

Data sources

Reserve transfers

- real-time bank-level reserve transfers (from *Fedwire Funds Service*)
- "bank" = bank holding company
- trading days, between 9:00am–6:30pm
- *Furfine algorithm* to identify:
  - *loans* (overnight)
  - *payments* (unrelated to loans)

Reserve balances

- end-of-day balances from FRB MPOA

Reserve requirements

- bank-level Regulation-D requirements from FRB MPOA (biweekly)
- Liquidity Coverage Ratio (LCR) from S&P Global Capital IQ (quarterly)

Bank types: sample sizes

Year	F	M	S	G	Total
2006	4	22	716	12	754
2014	4	15	373	12	404
2017	4	18	362	11	395
2019	4	18	379	11	412

- "Bank" = Bank Holding Company

Fed funds trading network (description)

- v^e_{mh} : value of all loans extended by bank m in maintenance period h
- v^r_{mh} : value of all loans received by bank m in maintenance period h
- $v_h = \sum_m v^e_{mh}$ value of all loans traded in maintenance period h

Participation rate (PR) for bank type $i \in \{F, M, S, G\}$

- $\mathcal{P}_{ih} = \sum_{m \in i} \frac{v^e_{mh} + v^r_{mh}}{2v_h}$: PR of type i in maintenance period h
- $\mathcal{P}_i$: yearly average of $\mathcal{P}_{ih}$ over maintenance periods

Reallocation index (RI) for bank type $i \in \{F, M, S, G\}$

- $\mathcal{R}_{ih} = \frac{\sum_{m \in i} v^e_{mh} - \sum_{m \in i} v^r_{mh}}{\sum_{m \in i} v^e_{mh} + \sum_{m \in i} v^r_{mh}}$: RI of bank type i in maintenance period h
- $\mathcal{R}_i$: yearly average of $\mathcal{R}_{ih}$ over maintenance periods

Fed funds trading network (description)

- Node labeled i represents the set of banks of type $i \in \{F, M, S, G\}$
- Arrow from node i to node j represents loans from type-i to type-j banks
- Node size: proportional to trade volume between banks of the that type
- Arrow width: proportional to trade volume between types joined by arrow
- Arrow and node colors depend on size of spread between (volume-weighted average) interest rate on loans between the two types, and the EFFR:
  - light blue: rate-EFFR spread in the 1^{st} quartile
  - dark blue: rate-EFFR spread in the 2^{nd} quartile
  - light red : rate-EFFR spread in the 3^{rd} quartile
  - dark red : rate-EFFR spread in the 4^{th} quartile

Interbank payments: estimation

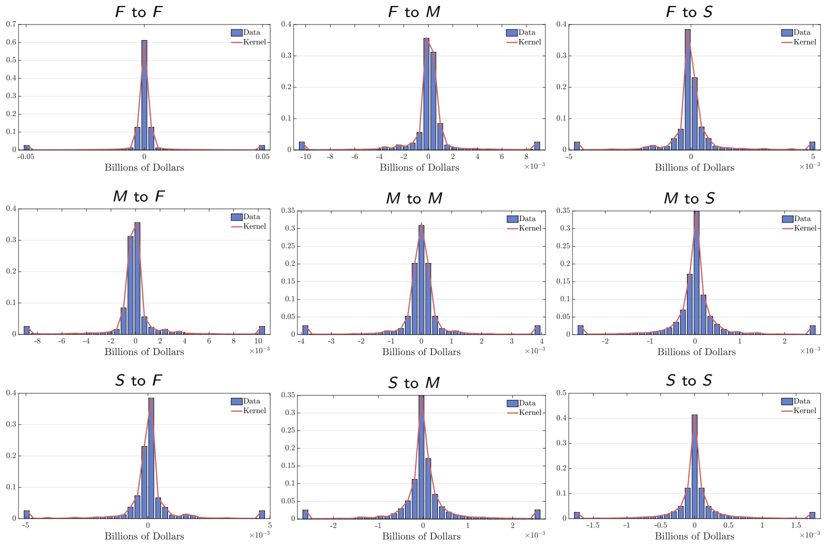
- $\mathbb{B}$: set of all banks
- $\mathbb{B}_i$: set of banks of type i
- N_i : number of banks of type i
- $\mathrm{s}_{mn}(t, d)$: value payments from bank m to bank n, in second t of day d
- $\bar{\mathrm{s}}_{mn}$: time-average of $\mathrm{s}_{mn}(t, d)$
- $\tilde{\mathrm{s}}_{mn}(t, d) \equiv \mathrm{s}_{mn}(t, d) - \bar{\mathrm{s}}_{mn}$: *payment shock* from m to n at time (t, d)
- $\mathrm{f}_m(t, d) \equiv \sum_{n \in \mathbb{B} \setminus \{m\}} \mathbb{I}_{\{\tilde{\mathrm{s}}_{mn}(t,d) \neq 0\}}$
- $\bar{\mathrm{f}}_m$: time-average of $\mathrm{f}_m(t, d)$

- For $i, j \in \{F, M, S\}$, G_{ij} is the Gaussian kernel density estimate of

$$\tilde{\mathbb{S}}^{ij} = \left\{\tilde{\mathrm{s}}_{mn}(t, d) : m \in \mathbb{B}_i, n \in \mathbb{B}_j \text{ for all } (t, d)\right\}$$

- For $i \in \{F, M, S\}$, set $\lambda_i = \frac{1}{N_i} \sum_{m \in \mathbb{B}_i} \bar{\mathrm{f}}_m$

Size distributions of payment shocks (2006)



Beginning-of-day distribution of reserves: calculations

- a^T_{md} : EOD (6:30 pm) reserves of bank m on day d (MPOA)
- s_{md} : net repayment by bank m on day d of $d-1$ loans (Fedwire)
- $\mathrm{a}_{md} \equiv \mathrm{a}^T_{md-1} - \mathrm{s}_{md}$: BOD (9:30 am) *basic reserves* of bank m on day d
- a_{mh} : average a_{md} over days d in maintenance period h
- $\underline{\mathrm{a}}^D_{mh}$: Regulation-D reserve requirement for bank m in period h (MPOA)
- $\underline{\mathrm{a}}^L_{mh}$: LCR requirement for bank m in maintenance period h details
- $\mathrm{x}_{mh} \equiv \mathrm{a}_{mh} - \underline{\mathrm{a}}^D_{mh} - \underline{\mathrm{a}}^L_{mh}$: *adjusted excess* reserves of bank m in period h
- $\hat{s}_{mn}$: average size of net daily payment from bank m to n in a given year
- $\mathrm{q}_{mh} \equiv \mathrm{x}_{mh} - \sum_n \hat{s}_{mn}$: average (over days in period h) BOD (9:30 am) *unencumbered reserves* of bank m

For $i \in \{F, M, S\}$, f^i_0 is the Gaussian kernel density estimate of

$$\mathbb{Q}^i = \{\mathrm{q}_{mh} : m \in \mathbb{B}_i \text{ for all } h\}$$

where $\mathbb{B}_i$ is the set of banks of type i

Liquidity Coverage Ratio (LCR)

- L_{mh} : net cash outflows in a 30-day stress scenario for bank m in period h
- H_{mh} : *High Quality Liquid Assets* (excess reserves, Treasury securities,...)
- $\mathrm{LCR}_{mh} \equiv \mathrm{H}_{mh}/\mathrm{L}_{mh}$: *Liquidity Coverage Ratio*
- Regulation: $1 \leq \mathrm{LCR}_{mh}$ (*daily* for large banks, *monthly* for others)

Problem

What quantity of reserves do banks treat as "required" to meet the LCR?

Liquidity Coverage Ratio (LCR)

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Problem

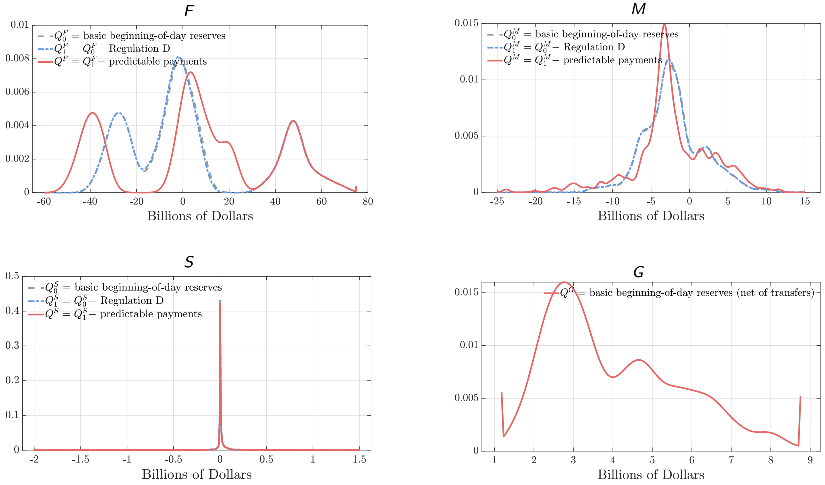
What quantity of reserves do banks treat as "required" to meet the LCR?

Our approach

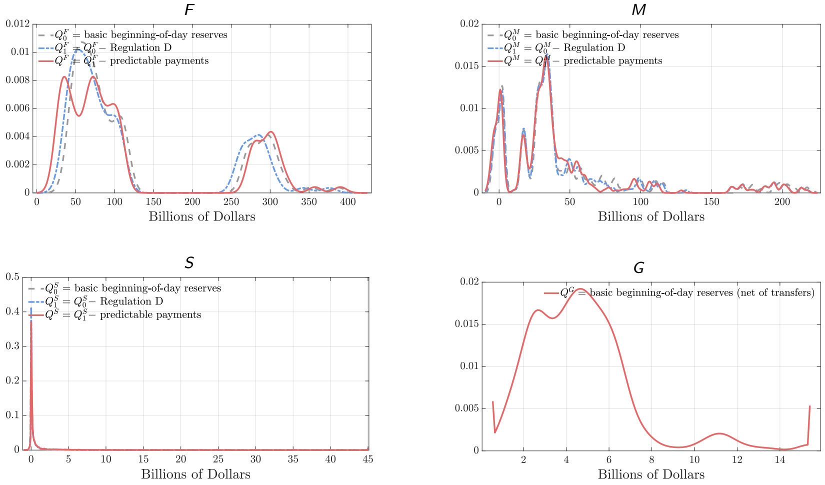
LCR-required reserves = smallest quantity of reserves needed to meet LCR:

- $A_{mh} \equiv H_{mh} - \max\left(0, a_{mh} - \underline{a}^D_{mh}\right)$
  qualifying HQLA *other than* reserves (a_{mh}) in excess of Regulation-D requirement ($\underline{a}^D_{mh}$)
- $\underline{a}^L_{mh} = \max\left(0, L_{mh} - A_{mh}\right)$ → our measure of *LCR-required reserves*
- $x_{mh} \equiv a_{mh} - \underline{a}^D_{mh} - \underline{a}^L_{mh}$ → our comprehensive measure of *excess reserves*

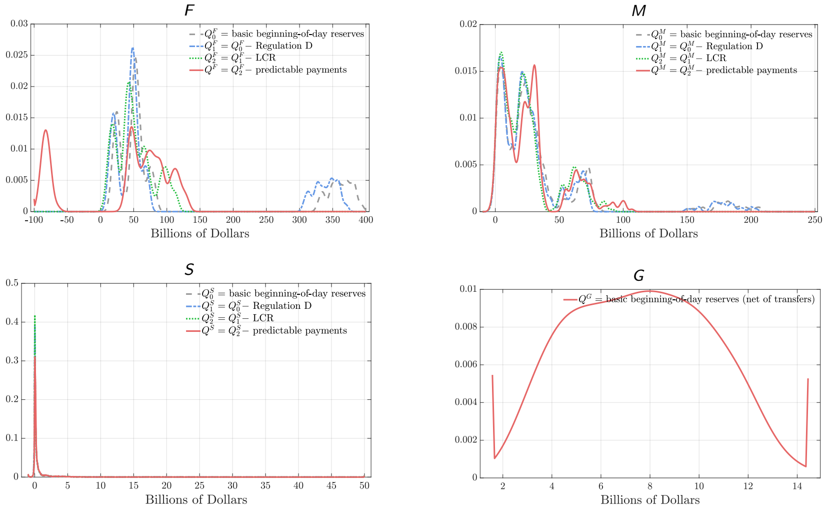
Beginning-of-day distributions of reserves (2006)



Beginning-of-day distributions of reserves (2014)



Beginning-of-day distributions of reserves (2017)



Reserve-draining Shocks

Reserve-draining shocks: examples

- Transactions between private-sector bank accounts and the Treasury General Account
  - tax payments
  - settlement of primary purchases of Treasury securities
- Repos involving foreign entities
- Changes in the quantity of currency in circulation
- Federal Reserve “float”

Reserve-draining shocks: estimation

- A_d: total reserves at the end of day d
- $\overline{\mathrm{A}}_d \equiv \frac{1}{41} \sum_{k=-20}^{20} \mathrm{A}_{d+k}$: moving average (40-day, two-sided)
- $\mathrm{z}_d \equiv \mathrm{A}_d - \overline{\mathrm{A}}_d$

The distribution of reserve-draining shocks is the Gaussian kernel density estimate of

$$\mathbb{Z} = \{\mathrm{z}_d : d \in \mathbb{D}\}$$

where $\mathbb{D}$ is the collection of all trading days during January 2011-July 2019

Liquidity effect: background on identification

Identification problem

To estimate the liquidity effect, want "exogenous variation" in the supply of reserves, but in some operating frameworks (e.g., corridor system) the Fed changes the supply of reserves in response to variations in the fed funds rate.

- Hamilton (1997) uses deviations between the actual end-of-day balance of the Treasury's Fed account and an empirical forecast of the end-of-day balance of the Treasury's Fed account as a proxy for unexpected changes in the quantity of reserves
- Carpenter and Demiralp (2006) replace Hamilton's instrument with the difference between the realized quantity of reserves on a given day, and the forecast for the quantity of reserves for that day that is used by the Desk to perform its daily accommodative open-market operations
- Afonso, Giannone, La Spada, Williams (2022) replace Hamilton's forecasting model of the Treasury's Fed account with a more flexible forecasting model of the joint dynamics of the quantity and price of reserves

Liquidity Effect

Liquidity effect: comparison with other studies

- Hamilton (1997)
  - sample period: 1989/04/06–1991/11/27
  - \$1 bn decrease in Q_t $\Rightarrow$ EFFR increases by 1 bp–2 bps
- Carpenter and Demiralp (2006)
  - sample period: 1989/05/19–2003/06/27
  - \$1 bn decrease in Q_t $\Rightarrow$ EFFR increases by 1 bp–2 bps
- Afonso, Giannone, La Spada, Williams (2022) (time-varying, 2009–2021)
  - sample period: 2019/01/01–2019/12/31
  - \$1 bn decrease in Q_t $\Rightarrow$ EFFR increases by 0.0059 bps
- Lagos-Navarro
  - sample period: 2019/01/01–2019/09/13
  - \$1 bn decrease in Q_t $\Rightarrow$ EFFR increases by 0.0062 bps

Liquidity effect: controlling for administered spreads

$$s_t - s_{t-1} = \gamma_0 + \gamma(Q_t - Q_{t-1}) + \varepsilon_t$$

Sample period: 2019/05/02–2019/09/13 (our baseline)

- Constant administered spreads:

  DWR-ONRRP = 75 bps and IOR-ONRRP = 10 bps

$\Rightarrow$ $\gamma = -0.0119$

Sample period: 2019/01/01–2019/09/13 (e.g., Afonso et al. (2022))

- Two configurations of administered spreads:

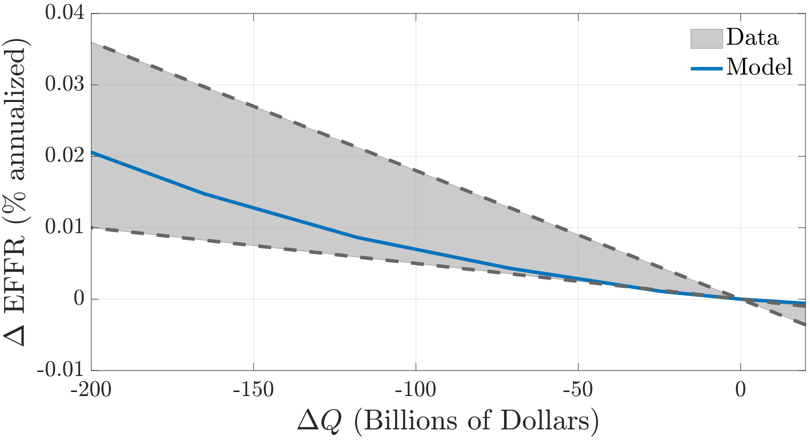
  2019/05/02–2019/09/13: DWR-ONRRP = 75 bps and IOR-ONRRP = 10 bps

  2019/01/01–2019/05/01: DWR-ONRRP = 75 bps and IOR-ONRRP = 15 bps

$\Rightarrow$ $\gamma = -0.0062$

Liquidity effect: model and data

calibration



Active Excess Reserves vs. Total Reserves

Active Excess Reserves & Total Reserves: definitions

- To calibrate the model we use an empirical measure of reserves that is:
  - net of predictable transfers, Regulation-D, and LCR requirements
  - only aggregates banks with nonzero fed funds trade in our sample

Active Excess Reserves & Total Reserves: definitions

- *Active Excess Reserves*
  - net of predictable transfers, Regulation-D, and LCR requirements
  - only aggregates banks with nonzero fed funds trade in our sample

☞ relevant measure of aggregate reserves for the theory

Active Excess Reserves & Total Reserves: definitions

- *Active Excess Reserves*
  - net of predictable transfers, Regulation-D, and LCR requirements
  - only aggregates banks with nonzero fed funds trade in our sample

☞ relevant measure of aggregate reserves for the theory

- *Total Reserves*
  - gross of predictable transfers, Regulation-D, and LCR requirements
  - aggregates all banks with reserve balances at the Fed

☞ well-known, easily available measure of aggregate reserves

Active Excess Reserves & Total Reserves: definitions

- *Active Excess Reserves*
  - net of predictable transfers, Regulation-D, and LCR requirements
  - only aggregates banks with nonzero fed funds trade in our sample

☞ relevant measure of aggregate reserves for the theory

- *Total Reserves*
  - gross of predictable transfers, Regulation-D, and LCR requirements
  - aggregates all banks with reserve balances at the Fed

☞ well-known, easily available measure of aggregate reserves

	Active Excess Reserves	Total Reserves
2017	$1,150.86 bn	$2,254.27 bn
2019	$910.73 bn	$1,568.27 bn

Active Excess Reserves & Total Reserves: "translation"

- Want to map *Total Reserves* (Q_t^D) into *Active Excess Reserves* (Q_t^M)
- Could just work with Q_t^M, but want to relate it to Q_t^D, but:
  - Q_t^D is better known and publicly available
  - we sometimes want to overlay empirical observations for Q_t^D on the theoretical demand for reserves, which is computed for Q_t^M

Summary

- We know:
  - a sample $\{Q_t^D\}_{t\in\mathbb{T}}$ for some period $\mathbb{T}$, along with its mean $\bar{Q}_{\mathbb{T}}^D$
  - $\bar{Q}_{\mathrm{Y}}^D$ and $\bar{Q}_{\mathrm{Y}}^M$ for two base years, $\mathrm{Y} \in \{\mathrm{Y}_0, \mathrm{Y}_1\}$
    ($\bar{Q}_{\mathrm{Y}}^D$ is the mean of $\{Q_t^D\}_{t\in\mathrm{Y}}$, and $\bar{Q}_{\mathrm{Y}}^M$ the mean of $\{Q_t^M\}_{t\in\mathrm{Y}}$)
- We want to "translate" a given sample $\{Q_t^D\}_{t\in\mathbb{T}}$ into a sample $\{Q_t^M\}_{t\in\mathbb{T}}$

Active Excess Reserves & Total Reserves: "translation"

Mapping between *Total Reserves* (Q_t^D) and *Active Excess Reserves* (Q_t^M)

Given $\{\bar{Q}_{\mathrm{Y}}^D, \bar{Q}_{\mathrm{Y}}^M\}_{\mathrm{Y}\in\{\mathrm{Y}_0,\mathrm{Y}_1\}}$ and a sample $\{Q_t^D\}_{t\in\mathbb{T}}$ for some period $\mathbb{T}$ with mean $\bar{Q}_{\mathbb{T}}^D$, construct the sample $\{Q_t^M\}_{t\in\mathbb{T}}$ as follows:

$$Q_t^M \equiv Q_t^D - \bar{Q}_{\mathbb{T}}^D + \bar{Q}_{\mathbb{T}}^M \quad \text{for each } t \in \mathbb{T}$$

with $\bar{Q}_{\mathbb{T}}^M$ given by

$$\bar{Q}_{\mathbb{T}}^M \equiv \omega \bar{Q}_{\mathrm{Y}_1}^M + (1-\omega)\,\bar{Q}_{\mathrm{Y}_0}^M$$

where $\omega \in \mathbb{R}$ is the value that satisfies

$$\bar{Q}_{\mathbb{T}}^D = \omega \bar{Q}_{\mathrm{Y}_1}^D + (1-\omega)\,\bar{Q}_{\mathrm{Y}_0}^D$$

Implicit assumption: variation in Q_t^D in sample $\mathbb{T}$ does not reflect changes in reserve requirements nor in the reserves of banks that are inactive in the fed funds market

ω-Rule

Counterfactuals for Q: our approach

- Estimate BOD distributions $\left\{\bar{F}^i_{\mathrm{Y}_0}, n^i_{\mathrm{Y}_0}, \bar{F}^i_{\mathrm{Y}_1}, n^i_{\mathrm{Y}_1}\right\}_{i\in\mathbb{N}}$ for years Y_0 and Y_1
- Let $x^i_{\mathrm{Y}}(p_n)$ be the n^{th} quantile of $\bar{F}^i_{\mathrm{Y}}$
- For any $\omega \in \mathbb{R}$, define:

$$\bar{n}^i_{\mathrm{Y}_\omega} \equiv \omega \bar{n}^i_{\mathrm{Y}_1} + (1-\omega)\,\bar{n}^i_{\mathrm{Y}_0}$$

$$\bar{F}^i_{\mathrm{Y}_\omega}(a) \equiv \sum_{\{p_n : x_{\mathrm{Y}_\omega}(p_n) \leq a\}} (p_n - p_{n-1})$$

where

$$x^i_{\mathrm{Y}_\omega}(p_n) \equiv \omega x^i_{\mathrm{Y}_1}(p_n) + (1-\omega)\, x^i_{\mathrm{Y}_0}(p_n)$$

is an interpolated quantile; the corresponding supply of reserves is

$$Q_{\mathrm{Y}_\omega} \equiv \sum_{i\in\mathbb{N}} \bar{n}^i_{\mathrm{Y}_\omega} \int a\, d\bar{F}^i_{\mathrm{Y}_\omega}(a)$$

We vary the supply of reserves (Q_{Y_ω}) by varying ω

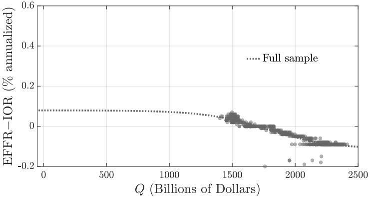
Our Demand Estimation

vs.

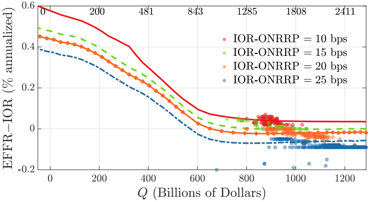
others

Estimation: model vs. $s_t = \underline{s} + \frac{\bar{s} - \underline{s}}{1 + e^{(Q_t - Q_0)\xi}}$

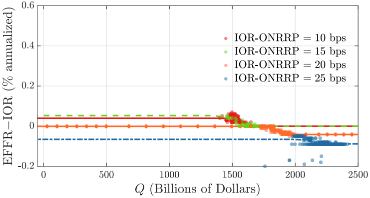
Reduced-form estimate, no theory



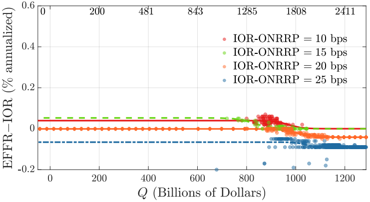
Quantitative-theoretical estimate



Reduced-form estimate, minimal theory

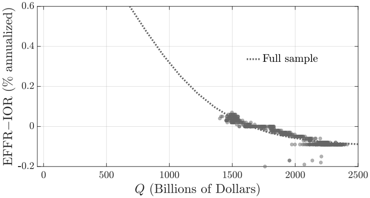


Reduced-form estimate, minimal theory

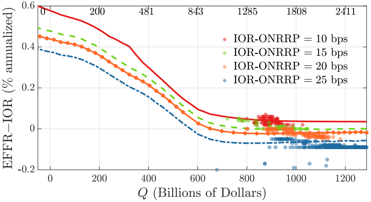


Estimation: model vs. $s_t = \underline{s} + \frac{\overline{s} - \underline{s}}{1 + e^{(Q_t - Q_0)\xi}}$ (version 2)

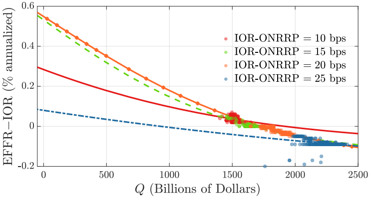
Reduced-form estimate, no theory



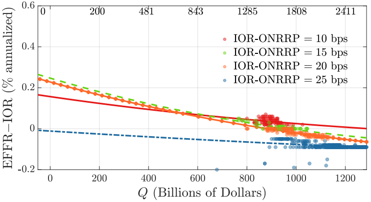
Quantitative-theoretical estimate



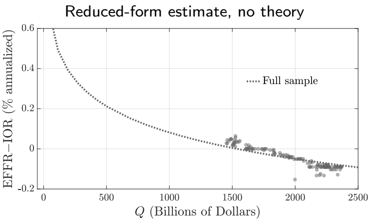
Reduced-form estimate, minimal theory

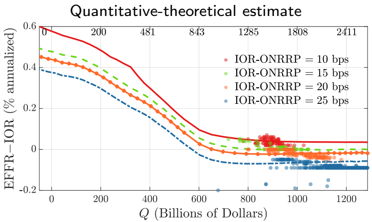


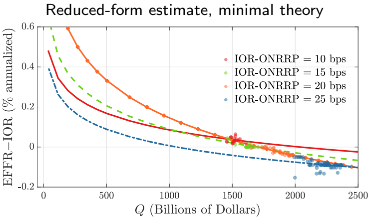
Reduced-form estimate, minimal theory

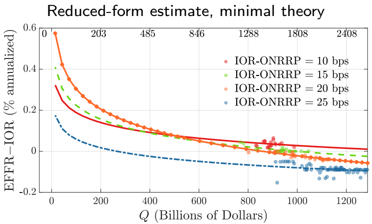


Estimation: model vs. $s_t = a + b \ln(Q_t) + c \ln(D_t)$



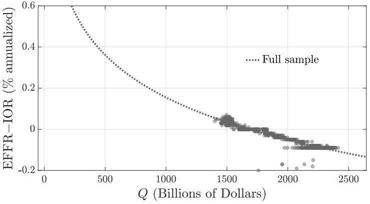




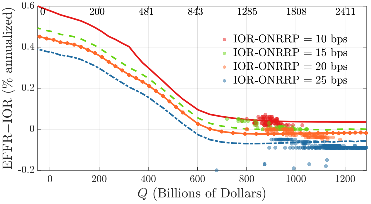


Estimation: model vs. $s_t = a + b \ln(Q_t)$

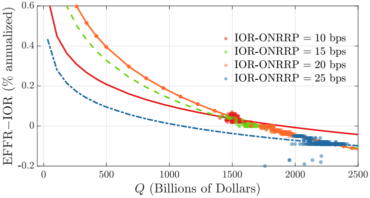
Reduced-form estimate, no theory



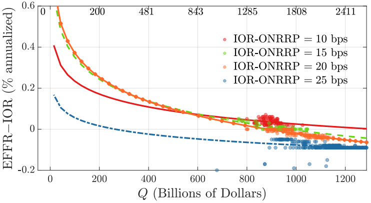
Quantitative-theoretical estimate



Reduced-form estimate, minimal theory

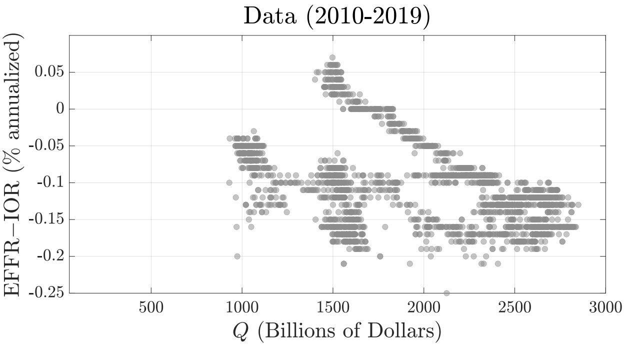


Reduced-form estimate, minimal theory



Discussion of LS-VJ

Can you spot a "demand for reserves"?



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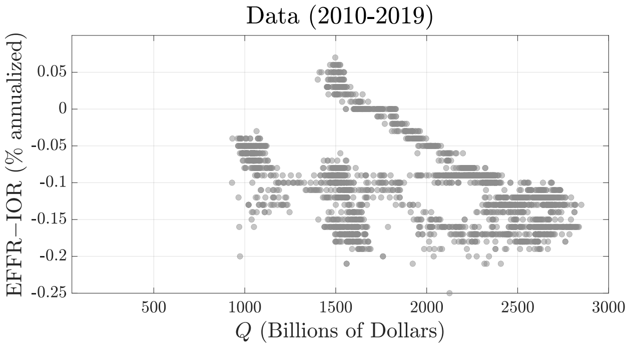


- LCR phased in between Jan 2015 and Jan 2017; SLR compliance since Jan 2018
- Afonso, Giannone, La Spada and Williams (2023) find structural *shifts*

$$\Rightarrow$$

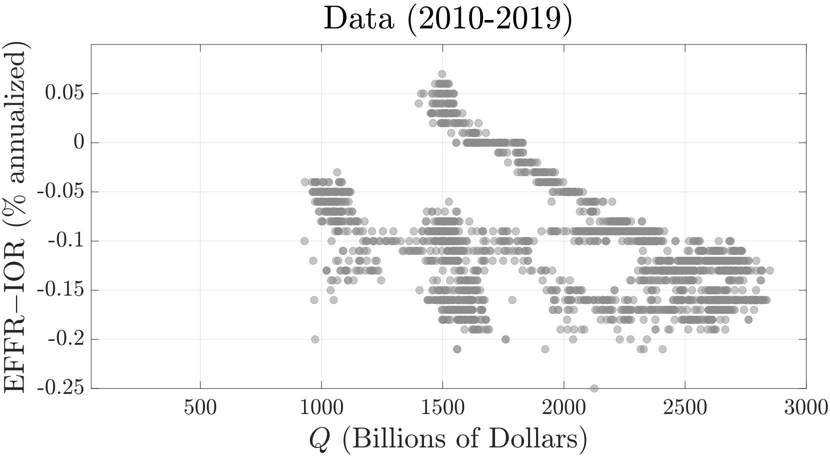
- Bad idea to simply run $EFFR - IOR = a + bf(Q)$ (e.g., $f(Q) = Q$, or $ln(Q)$)
- To identify "demand", need to control for structural factors behind these shifts

LSVJ proposal: $s_t = a + b\ln(Q_t) + c\ln(D_t)$

- $s_t \equiv EFFR_t - IOR_t$; Q_t : reserves; D_t : bank deposits
- LSVJ idea: more deposits $\Rightarrow$ banks more exposed to liquidity shocks (e.g., withdrawal uncertainty) $\Rightarrow$ shifts up reserve demand
- In a banking equilibrium, shocks to s_t affect D_t
- Proposed instrument: *household financial wealth*, but... why would it satisfy the appropriate exclusion restriction?
- Granting "exogenous" variation in D_t, is the magnitude of this deposit-driven precautionary motive for holding reserves plausible?
  - LSVJ regression $\Rightarrow \left.\frac{d\ln(Q_t)}{d\ln(D_t)}\right|_{s_t=\bar{s}} = -\frac{c}{b} \approx 2.13$
  - $Q_{2019} = \$1.7tn$, $D_{2019} = \$13tn \Rightarrow \frac{0.0213\times 1.7}{0.01\times 13} \approx 0.28$

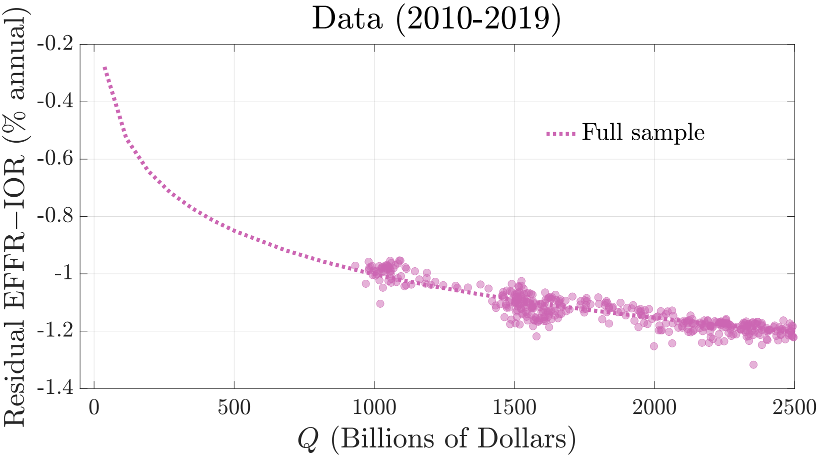
    $\Rightarrow$ 28 cents per dollar received in deposits is held as reserves to insure the idiosyncratic withdrawal risk of the deposit
  - Seems rather large...
    2000–2007: $Q_t/D_t < 0.01$ (above 0.2 for 2013–2016)
    ... maybe bulk of demand shift is not due to deposit growth?

What do we do about this?



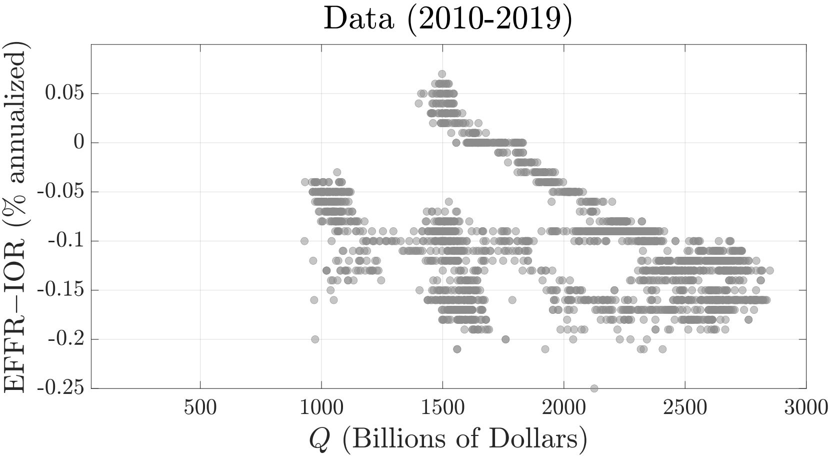
- 2010–2019, daily data

LS-VJ regression: $s_t = a + b\ln(Q_t) + c\ln(D_t)$



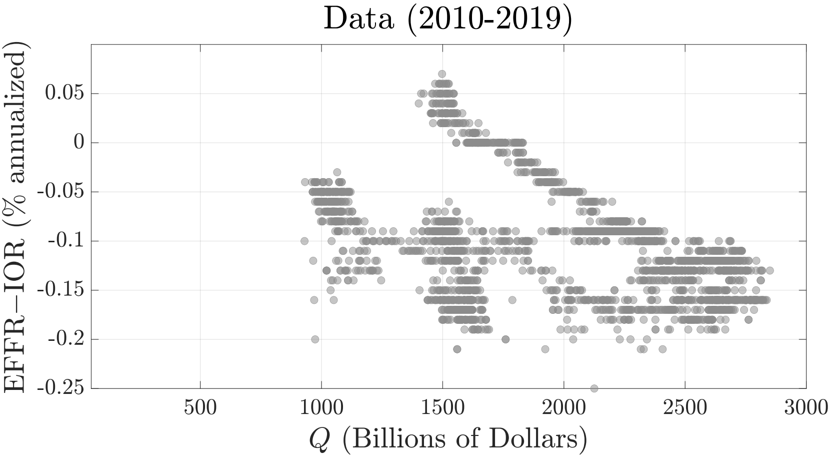
- 2010–2019, weekly data (D_t = demand deposits)
- OLS fit of $y_t \equiv s_t - a - b\ln(D_t)$ on Q_t

"It takes a demand shifter to beat a demand shifter"



- 2010–2019, daily data

IOR-ONRRP as demand shifter



- 2010–2019, daily data
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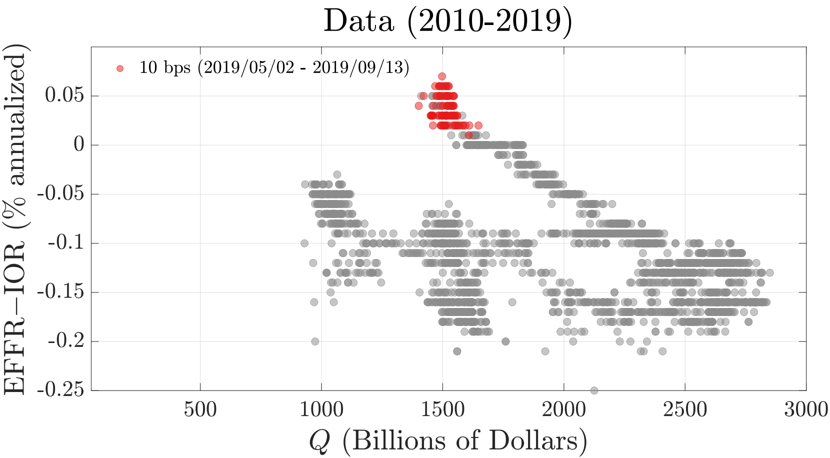
A bit of theory: identify IOR-ONRRP policy regimes



- 2010–2019, daily data split by IOR-ONRRP regime
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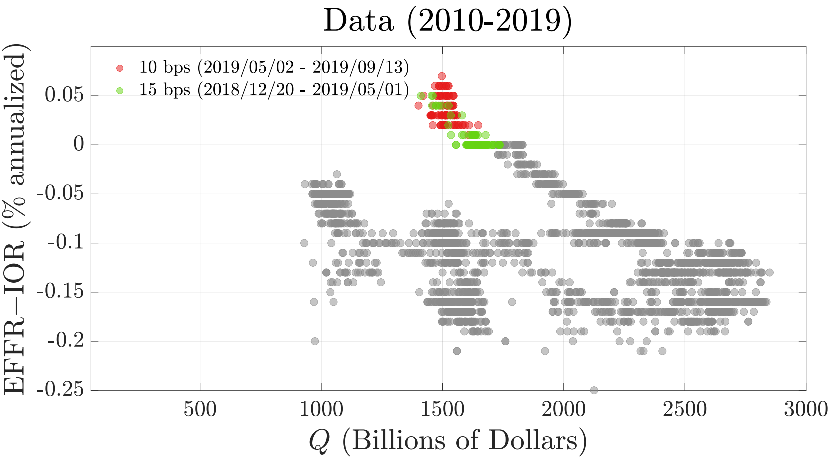

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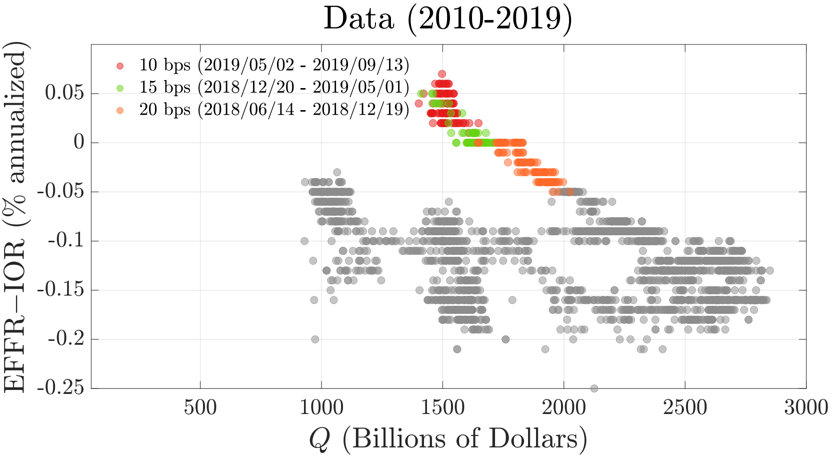

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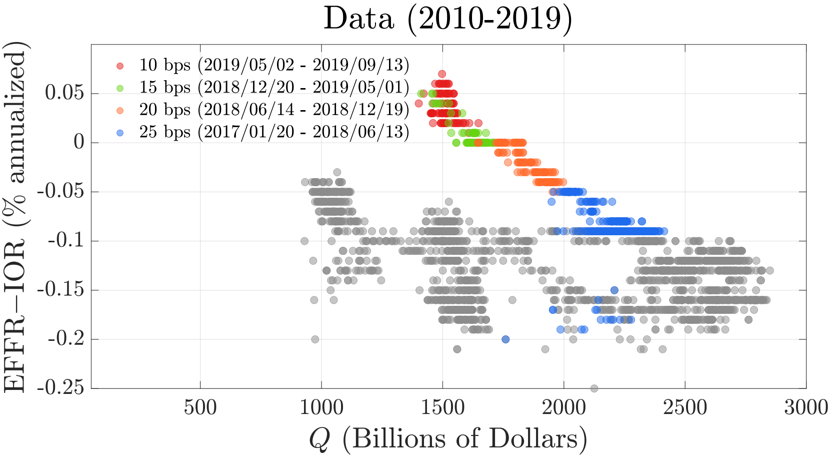

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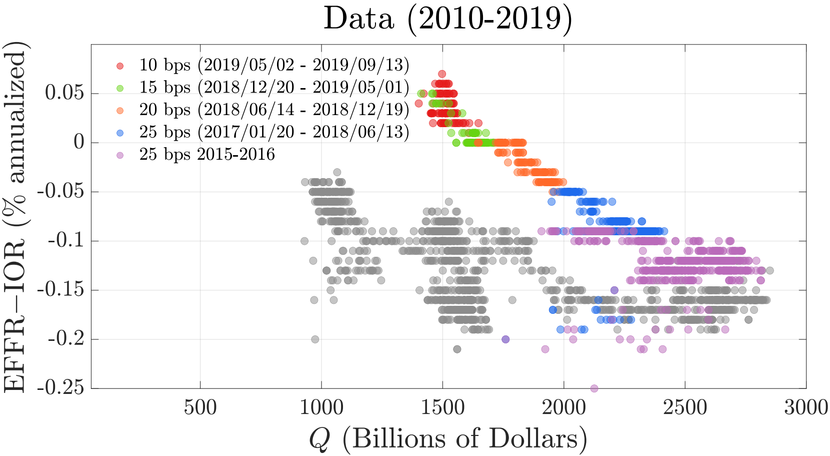
A bit of theory: identify IOR-ONRRP policy regimes



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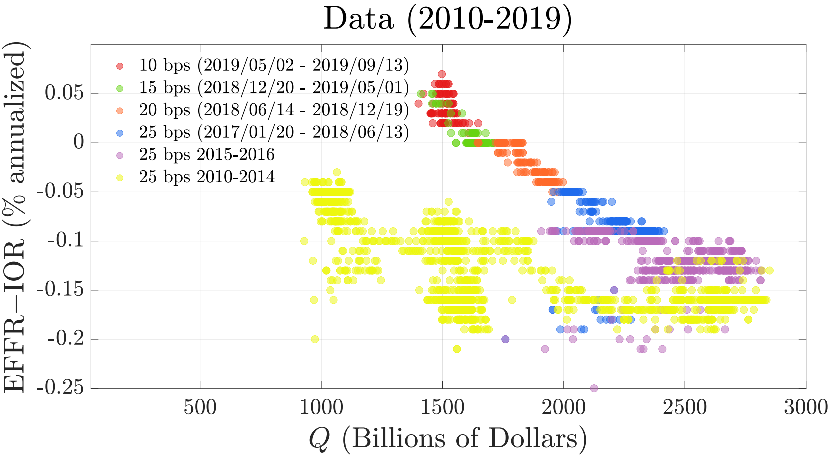

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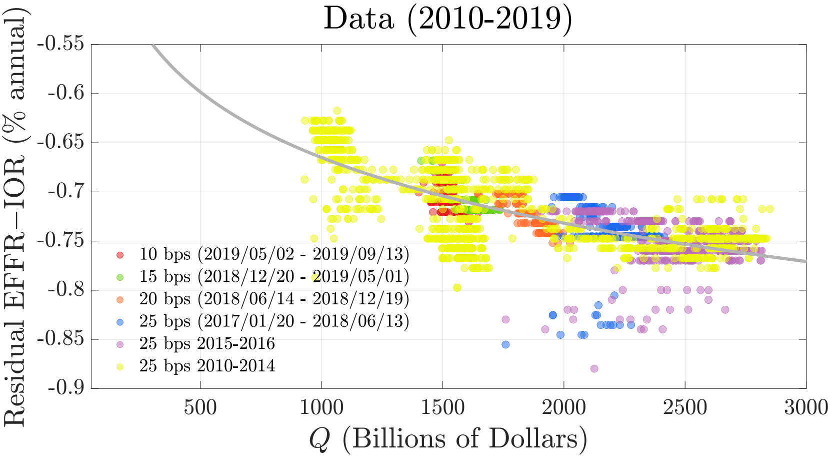
Alternative regression: $s_t = b \ln(Q_t) + \text{IOR-ONRRP dummies}$

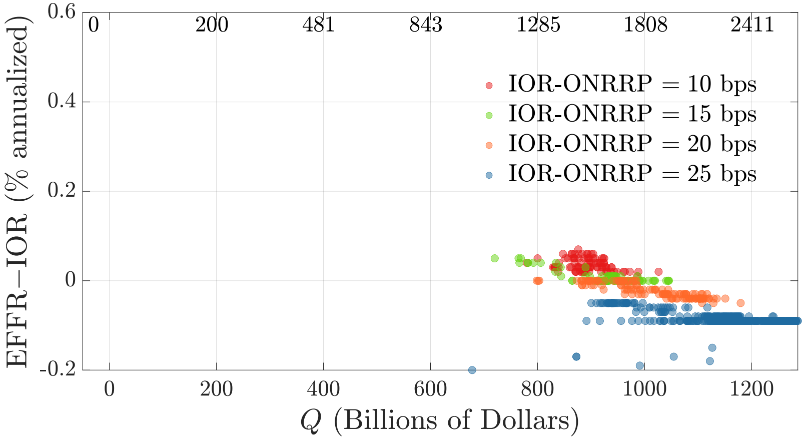


- 2010–2019, daily data split by IOR-ONRRP regime
- OLS fit of $y_t \equiv s_t - (\text{IOR-ONRRP dummies})$ on Q_t

Alternative demand estimations

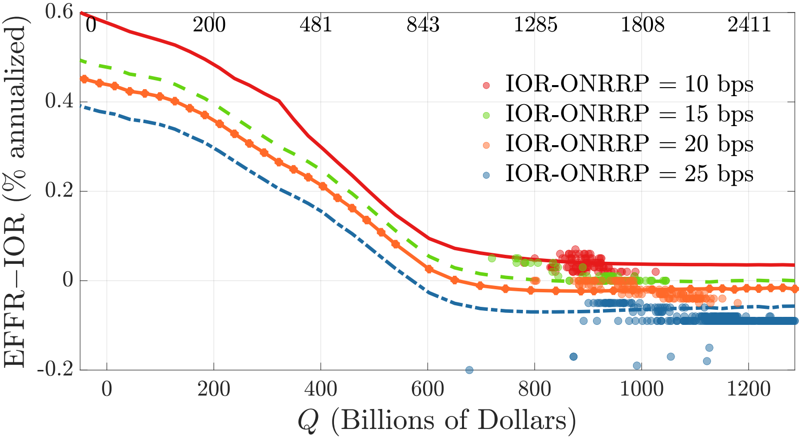
	(0)	(1)	(2)	(3)	(4)
$\ln(Q)$	-0.200	-0.219	-0.182	-0.156	-0.054
	(0.004)	(0.006)	(0.005)	(0.007)	(0.005)
$\ln(TD)$	0.363		0.320		
	(0.007)		(0.012)		
$\ln(DD)$		0.150		0.096	
		(0.005)		(0.005)	
$d_{25\text{bps}}$	no	no	yes	yes	yes
$d_{20\text{bps}}$	no	no	yes	yes	yes
$d_{15\text{bps}}$	no	no	yes	yes	yes
$d_{10\text{bps}}$	no	no	yes	yes	yes
R^2	0.85	0.70	0.97	0.95	0.92
obs	506	506	506	506	506

Quantitative-theoretic estimation



- Sample 2017/01/20–2019/09/13 split by IOR-ONRRP regime

Quantitative-theoretic estimation



- Sample 2017/01/20–2019/09/13 split by IOR-ONRRP regime
- ADR implied by the theory (baseline calibration, but with administered rates to match the subsample)

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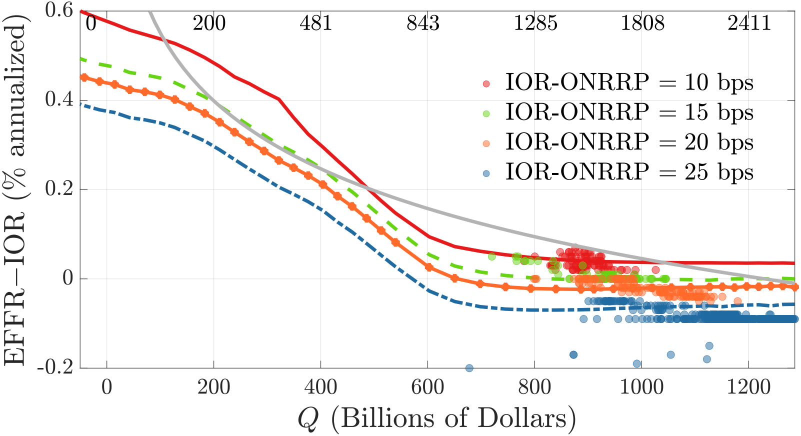

- Sample 2017/01/20–2019/09/13 split by IOR-ONRRP regime
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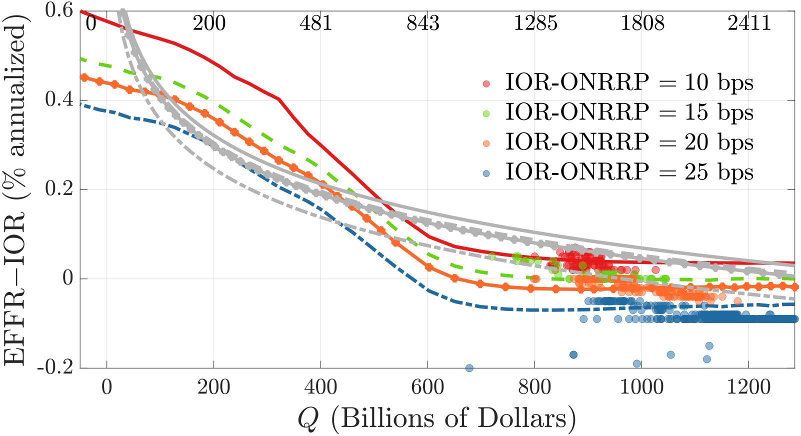
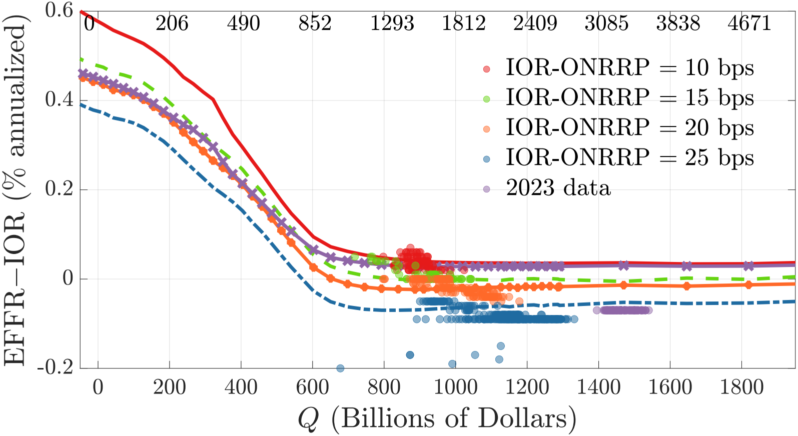


- Sample 2017/01/20–2019/09/13 split by IOR-ONRRP regime
- ADR implied by the theory (baseline calibration, but with administered rates to match the subsample)
- LS-VJ fit (2010-2019 sample, with demand deposits as control, and IOR-ONRRP-regime dummies)

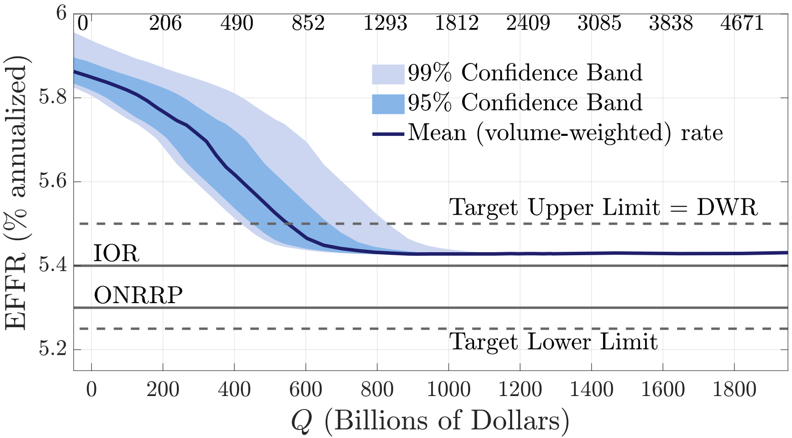
Demand Estimation for 2023

Quantitative-theoretic estimation (with 2023 data)



- ADR implied by the theory (baseline calibration, with administered rates to match the subsample)
- "2023 data": 2023/08/01–2023/12/31, with TRL = 5.25%; ONRRP = 5.30%; IOR = 5.40%; DWR = TRU = 5.50%

Monetary Confidence Band (year 2023)



- Baseline calibration but with administered and target rates as in 2023/08/01–2023/12/31: TRL = 5.25%; ONRRP = 5.30%; IOR = 5.40%; DWR = TRU = 5.50%

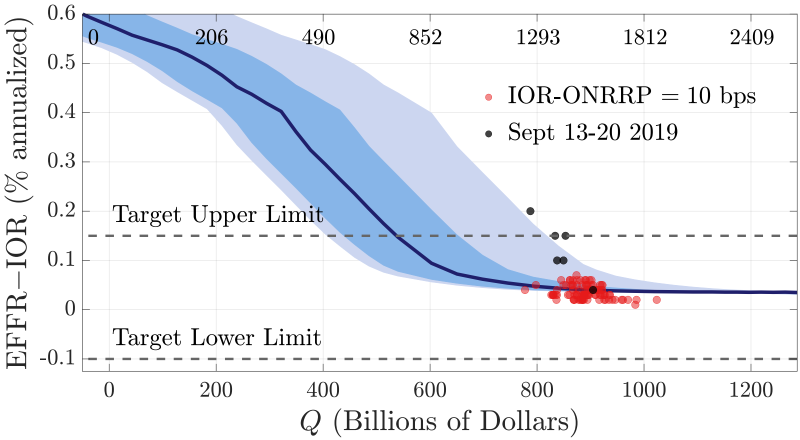
September 17, 2019

The money-market events of September 17, 2019

Day	Administered Rates					EFFR	EFFR-IOR	ΔQ_t	Fed Repo
	ONRRP	IOR	DWR	TRL	TRU				
September 13 (Friday)	2.00	2.10	2.75	2.00	2.25	2.14	0.04	-51.50	0
September 16 (Monday)	2.00	2.10	2.75	2.00	2.25	2.25	0.15	-65.72	0
September 17 (Tuesday)	2.00	2.10	2.75	2.00	2.25	2.30	0.20	46.30	53
September 18 (Wednesday)	2.00	2.10	2.75	2.00	2.25	2.25	0.15	3.67	75
September 19 (Thursday)	1.70	1.80	2.50	1.75	2.00	1.90	0.10	11.94	75
September 20 (Friday)	1.70	1.80	2.50	1.75	2.00	1.90	0.10	3.15	75

- 2019/09/17: first upward deviation from target in 11 years
- Aren't $1.3 tn of reserves "ample enough" to run a floor system?

The money-market events of September 17, 2019



- Sample period: 2017/01/20–2019/09/13 ∪ 2019/09/16,17,18,19,20
- MCB is for the baseline calibration (which excludes 2019/09/16,17,18,19,20)

\$1.3 tn — not ample enough?

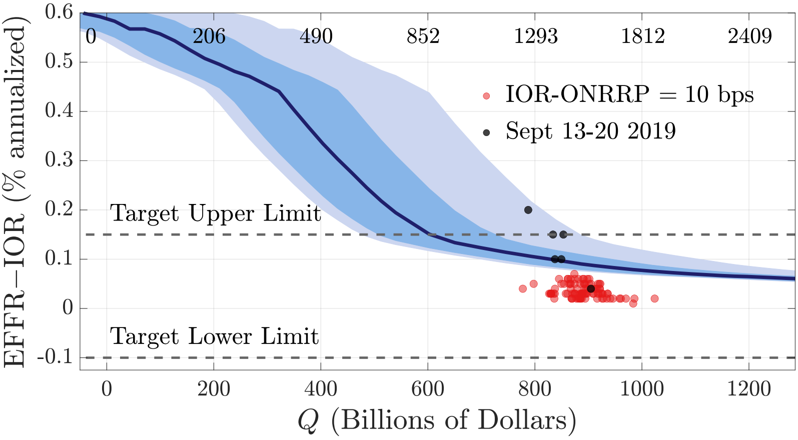
Jamie Dimon's "red line"

"As I said, we have \$120 bn in our checking account at the Fed, and it goes down to \$60 bn and then back to \$120 bn during the average day. But we believe the requirement under CLAR (Comprehensive Liquidity Analysis and Review) and resolution and recovery is that we need enough in that account, so if there's extreme stress during the course of the day, it doesn't go below zero. If you go back to before the crisis, you'd go below zero all the time during the day. So the question is, how hard is that as a red line?"

—Jamie Dimon, Chairman and CEO of JPMorgan Chase

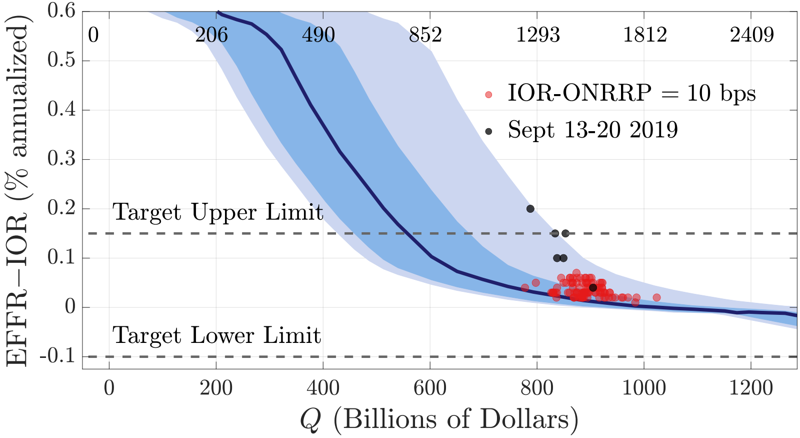
October 15, 2019 earnings call

2019/09/17: Jamie Dimon's "red line" (version 1)



- Sample period: 2017/01/20–2019/09/13 ∪ 2019/09/16,17,18,19,20
- MCB for baseline calibration but with $u_i(a) = \iota_d a \mathbb{I}_{\{a<0\}}$ for all i; $\iota_d = \frac{x}{800}\iota_w$, and $x = 0.1$

2019/09/17: Jamie Dimon's "red line" (version 2)



- Sample period: 2017/01/20–2019/09/13 ∪ 2019/09/16,17,18,19,20
- MCB for baseline calibration but with $\beta_F = 0$

Literature

Related literature

Fed funds market

Poole (1968); Hamilton (1996); Carpenter and Demiralp (2006); Ashcraft and Duffie (2007); Bech and Atalay (2010); Afonso, Kovner, and Schoar (2011); Bech and Klee (2011); Afonso and Lagos (2015); Ennis and Weinberg (2013); Armenter and Lester (2017); Afonso, Armenter, and Lester (2019); Beltran, Bolotnyy, and Klee (2021); Ennis (2019); Chiu, Eisenschmidt, and Monnet (2020); Copeland, Duffie, and Yang (2021); Afonso, Giannone, La Spada, and Williams (2022), Lopez-Salido and Vissing-Jorgensen (2023)

Search approach to OTC marketstructure

Duffie, Gârleanu, and Pedersen (2005); Lagos and Rocheteau (2007, 2009); Weill (2007); Lagos, Rocheteau, and Weill (2011); Üslü (2019); Hugonnier, Lester, and Weill (2020)

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Computation

Computation algorithm – outline

- Guess the distribution of balances
- Compute the value functions iterating backward, from the terminal condition. (This involves solving for the terms of trade and integrating over payment shocks at each time step.)
- Use the trade outcomes (and probabilities over payment shocks) to update the distribution of balances by iterating forward, from the initial condition
- Iterate until the distribution of balances has converged (or when a set of model moments has converged)