Monetary Policy Operations:

Theory, Evidence, and Tools for Quantitative Analysis

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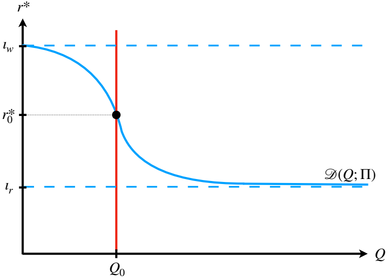
Monetary policy involves two steps

- Choice of operational target
- Implementation of target

Operating frameworks to implement a FFR target

Corridor system

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



- requires *local* demand estimates

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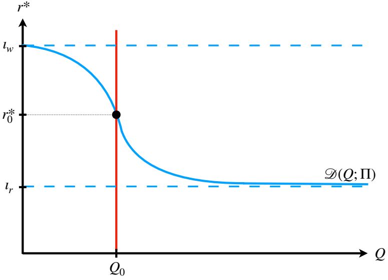
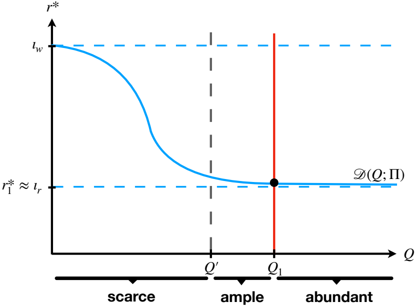


- requires *local* demand estimates

Floor system

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



- requires *global* demand estimates

Questions

answers

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?

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

- How does the demand look like for lower reserves?

New regulations since GFC (e.g.: LCR, SLR)...

- How does the demand look like under new regulation?

What we do: micro to macro approach

literature

- Document new micro and marketwide facts
- Develop the prototypical model of the federal funds market (e.g., Afonso and Lagos (2015)) by incorporating bank-level heterogeneity in:
  - payoffs
  - degree of centrality in market-making
  - frequency and size distributions of payment shocks
- 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 policy implementation

Roadmap

- Model: framework + intuition
- Evidence
- Calibration
- Results:

1. Global demand estimates
2. Empirical model(s)
3. Navigational tools
4. Sept 2019 events

Theory

The fed funds market

A market for loans of reserve balances held at the Federal Reserve

- What's traded?

  overnight unsecured loans

- How are they traded?

  over the counter

- Who trades?

  institutions that hold reserve balances at the Fed

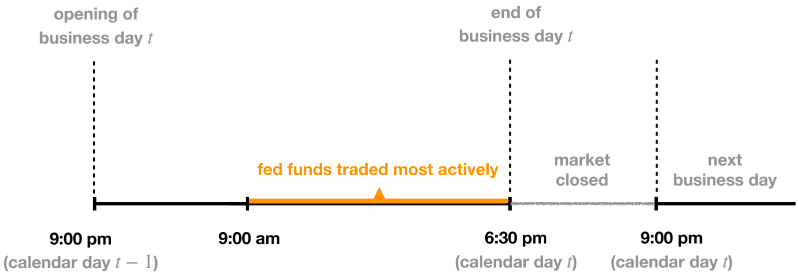
  e.g., commercial banks, GSEs, government agencies (federal and state governments), agencies and branches of foreign banks in the U.S., savings banks, thrift institutions, credit unions, government-securities dealers

- Trading motives?

  liquidity management, *earn interest*

  e.g., to offset payment shocks, meet desired cash holdings, comply with liquidity regulations, earn interest

Timeline


opening of
business day t
end of
business day t
fed funds traded most actively
market
closed
next
business day
9:00 pm
(calendar day $t-1$)
9:00 am
6:30 pm
(calendar day t)
9:00 pm
(calendar day t)

Model

bargaining equilibrium

- Continuous-time *trading day*, $t \in [0, T]$
- Heterogeneous *banks*
  - measure n_i of type i
  - initial balances distribution $a \sim F_0^i$
- *Loans: bilateral, OTC marketstructure*
  - *random meetings, Poisson rates* $\{\beta_i\}$
  - *loan and rates with Nash bargaining*
  - → *Key assumption:* $\beta_F >> \beta_M > \beta_S$
- *Payment shocks, bilateral and random*
  - *random meetings, Poisson rates* $\{\lambda_i\}$
  - *Payment distribution* $z \sim G^{ij}(z)$

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Fed Policy → *banks' payoffs*

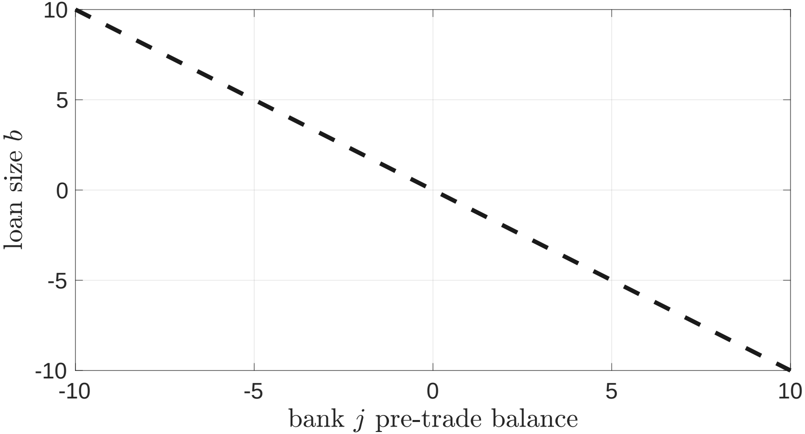
- End-of-day pay-off $\{U_i(a)\}_i$
  - if $a < \underline{a}_i \rightarrow \iota^{dwr}$: discount window rate
  - if $a \geq \underline{a}_i \rightarrow \iota_i^r$: rate on reserves
  - → $\iota_i^r \geq \iota_{GSE}^r$ (IOR>ONRRP)
- intraday pay-off $\{u_i(a)\}_i$
  - e.g: overdraft cost: $u_i < 0$ if $a < 0$

Intuition: simple example

- Two banks: F and S with $\beta_F = 10\beta_S$
- No payment shocks: $\lambda_i = 0$
- Reserve requirement $\underline{a}_i = 0$ (normalization)

$\rightarrow$ Trade of bank $j \in S$ with bank $i \in F$ with $a_i = 5$

Intuition: trade outcomes



Example: $\mathbb{N} = \{F, S\}$; $(n_F, n_S) = (0.03, 0.97)$; $(\beta_F, \beta_S) = (0.5, 0.05)$; $\lambda_i = 0$, $F_0^i \sim \mathcal{N}(0, 0.2)$, and $U_i(a) = (1 + \mathbb{I}_{\{0 \leq a\}} \bar{\imath}_r + \mathbb{I}_{\{a<0\}} \bar{\imath}_w)a$, for all $i \in \mathbb{N}$; $\bar{\imath}_r = 0.02/360$; $\bar{\imath}_w = 0.03/360$

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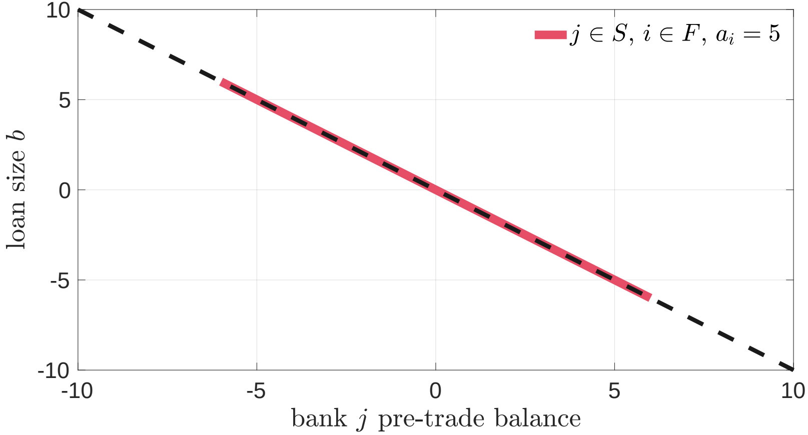

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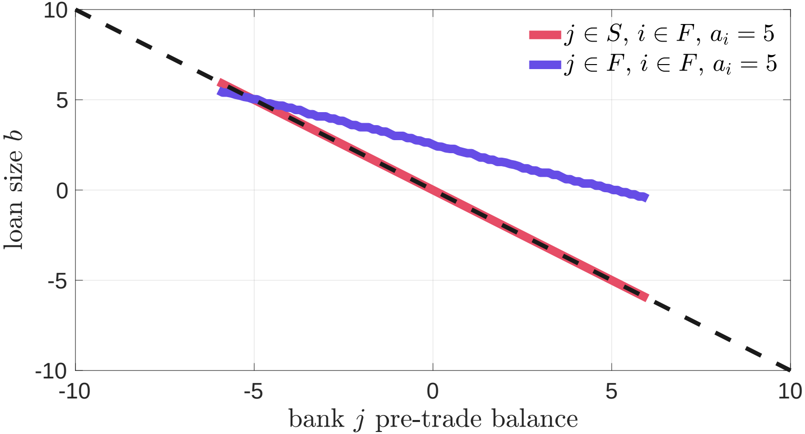

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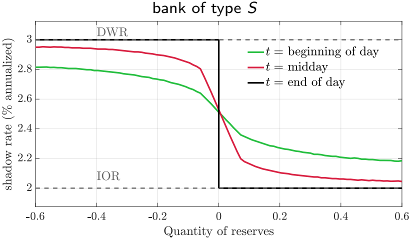
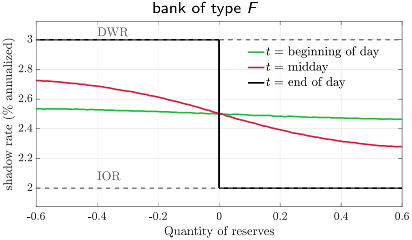
Intuition: shadow interest rates $= \frac{\partial V_t^i(a)}{\partial a} - 1$





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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. Reserve-draining shocks
5. *Liquidity effect* (local slope of reserve demand)

Fed funds trading activity

- Participation rate

$$\mathcal{P}_{nd} \equiv \frac{v^e_{nd} + v^r_{nd}}{v_d}$$

- Reallocation index

$$\mathcal{R}_{nd} \equiv \frac{v^e_{nd} - v^r_{nd}}{v^e_{nd} + v^r_{nd}}$$

- v^e_{nd} : value of all loans made by bank n in maintenance period d; $v_d \equiv \sum_n v^e_{nd}$
- v^r_{nd} : value of all loans received by bank n in maintenance period d
- $\mathcal{P}_n \equiv \frac{1}{D} \sum_d \mathcal{P}_{nd}$; $\mathcal{R}_n \equiv \frac{1}{D} \sum_d \mathcal{R}_{nd}$ (D maintenance periods in a year)

Fed funds trading activity

- Participation rate

$$\mathcal{P}_{nd} \equiv \frac{\upsilon^e_{nd} + \upsilon^r_{nd}}{2\upsilon_d}$$

- Reallocation index

$$\mathcal{R}_{nd} \equiv \frac{\upsilon^e_{nd} - \upsilon^r_{nd}}{\upsilon^e_{nd} + \upsilon^r_{nd}}$$

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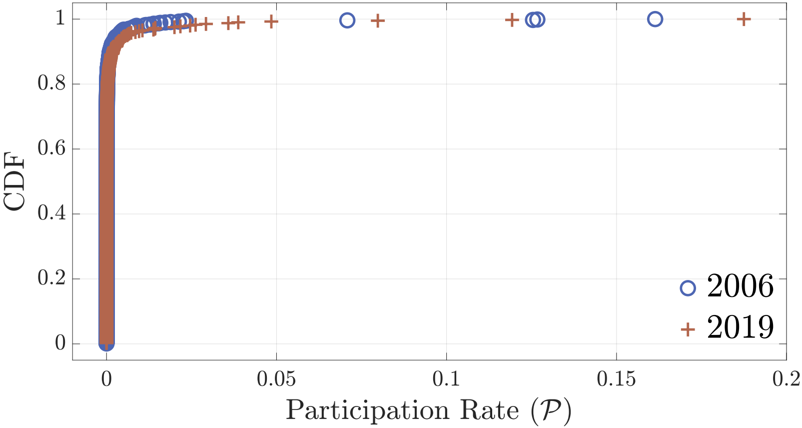
Use $\mathcal{P}_n$ to define four types $i \in \{F, M, S, GSE\}$

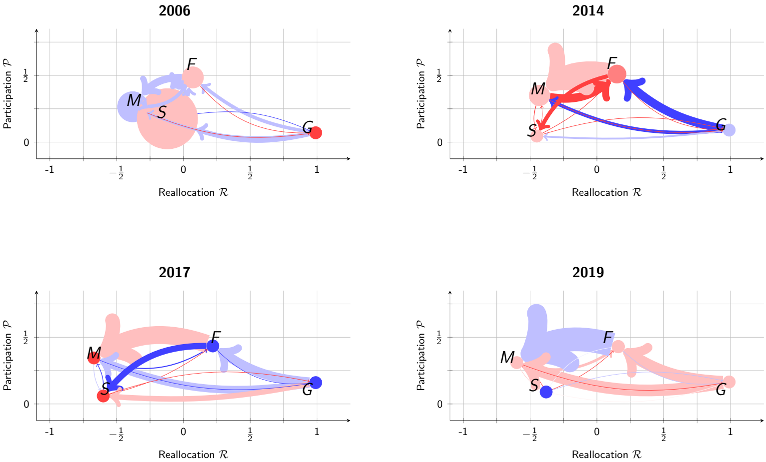
sample



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

Fed funds trading network

calculations



Calibration

Calibration: key moments

- *Sample period*: May-Sep 2019 (before 2019 events)
  - $+$ Latest period with all regulations in place
  - $+$ stable policy rates: $\iota^{dwr} = 3\%$, $\iota^{ior} = 2.35\%$, $\iota^{onrrp} = 2.25\%$
  - $\rightarrow$ $\iota^{ior} - \iota^{onrrp} = 10$ bps
- *Data*: balances distribution $\{n_i, F_0^i\}_i$ and payment shocks $\{\lambda_i, G^{ij}\}_i$
  - $\rightarrow$ $\lambda_F = 0.95$, $\lambda_M = 0.25$, $\lambda_S = 0.01$ (frequency $\times$ second)
- *Targets*: network + liquidity effect
  - $+$ pins down contact rates $\{\beta_i\}$
  - $+$ add borrowing costs $\{\kappa_i\}$
  - $+$ add stigma (ι^s) from discount window borrowing (Armantier et al., 2015)

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Primitives

Parameter	Description
$[0, T]$	trading day (800 periods $\times$ 42 secs $\approx$ 34,200 secs $\equiv$ 9.5 hs)
$\mathbb{N}$	set of bank types $= \{F, M, S, GSE\}$
$\{n_i\}_{i\in\mathbb{N}}$	proportion of banks of type i
$\{F_0^i\}_{i\in\mathbb{N}}$	beginning-of-day distribution of reserves
$\{\lambda_i\}_{i\in\mathbb{N}}$	payment-shock frequency
$\{G_{ij}\}_{i,j\in\mathbb{N}}$	size distributions of payment shocks
$\{\beta_i\}_{i\in\mathbb{N}}$	trading frequencies
$\underline{\theta}$	bargaining power: $\theta_{ij} = \underline{\theta}$ if $i \in \{GSE\}$ and $j \in \mathbb{N} \setminus \{GSE\}$ and $\theta_{ij} = 1/2$ otherwise
$\{\kappa_i\}_{i\in\mathbb{N}}$	proportional borrowing costs
r	discount rate ($r = 0$ in the baseline)
$\{u_i\}_{i\in\mathbb{N}}$	intraday payoffs
ι_d	$u_i(a) = \iota_d a \mathbb{I}_{\{a<0\}}$ (with $\iota_d = 0$ in the baseline)
$\{U_i\}_{i\in\mathbb{N}}$	end-of-day payoffs
$\bar{\iota}_r \equiv \iota_r + \iota_\ell$ $\bar{\iota}_w \equiv \iota_w + \iota_\ell + \iota_s$	$U_i(a) = \left(1 + \mathbb{I}_{\{0\le a\}}\bar{\iota}_r + \mathbb{I}_{\{a<0\}}\bar{\iota}_w\right) a$, for $i \in \{F, M, S\}$
$\bar{\iota}_o \equiv \iota_o + \iota_\ell$	$U_i(a) = \left(1 + \mathbb{I}_{\{0\le a\}}\bar{\iota}_o + \mathbb{I}_{\{a<0\}}\bar{\iota}_w\right) a$, for $i = GSE$

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
$n_{GSE} = 0.026$	proportion of financial institutions of type GSE	11/412	0.026
$\{F_0^i\}_{i\in\mathbb{N}}$	beginning-of-day distribution of reserves	estimated	estimated
$\lambda_F = 0.951$	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
$\lambda_{GSE} = 0$	bank-level share of unexpected payments per second for type GSE	0	0
$\{G_{ij}\}_{i,j\in\mathbb{N}}$	size distributions of payment shocks	estimated	estimated
$\iota_w = 0.0300/360$	DWR (3.00% per annum, primary credit; 2019/06/06–2019/07/31)	0.0300/360	0.0300/360
$\iota_r = 0.0235/360$	IOR (2.35% per annum; 2019/06/06–2019/07/31)	0.0235/360	0.0235/360
$\iota_o = 0.0225/360$	ONRRP (2.25% per annum; 2019/06/06–2019/07/31)	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., $\mathcal{P}_M$)	0.62	0.54
$\beta_S = 0.0007$	participation rate of financial institutions of type S (i.e., $\mathcal{P}_S$)	0.18	0.15
$\beta_{GSE} = 0.0036$	participation rate of financial institutions of type GSE (i.e., $\mathcal{P}_{GSE}$)	0.33	0.27
$\kappa_F = 0.039e\text{-}3$	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
$\kappa_{GSE} = 1.25e\text{-}3$	reallocation index of financial institutions of type GSE (i.e., $\mathcal{P}_{GSE}$)	1	1

ω rule liquidity effect

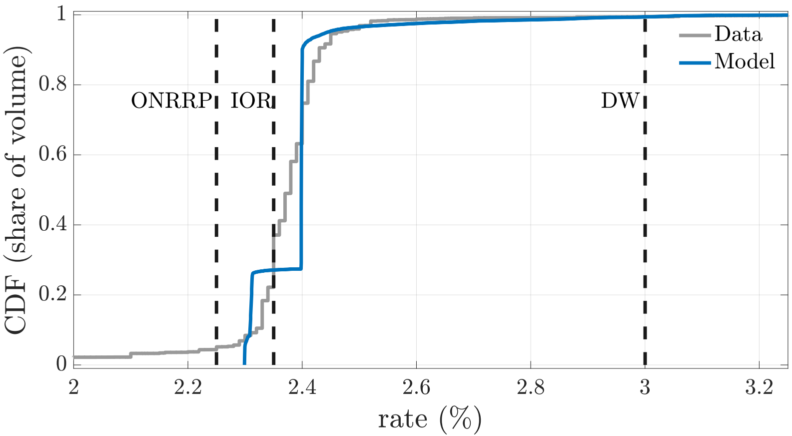
Validation

Model fit

Check model fit for prices and quantities not targeted in the calibration

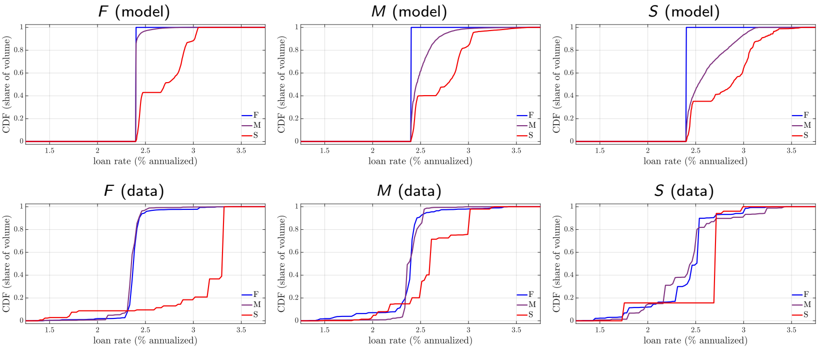
1. Distribution of loan rates
2. Conditional distribution of loan rates in excess of DWR
3. Bid-ask spread by bank type
4. Distributions of loan rates between pairs of bank types
5. Fed funds trading network

Distribution of loan rates



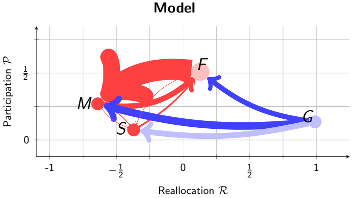
- Sample period: 2019/06/06–2019/07/31; ONRRP = 2.25%; IOR = 2.35%; EFFR = 2.39%; DWR = 3.0%

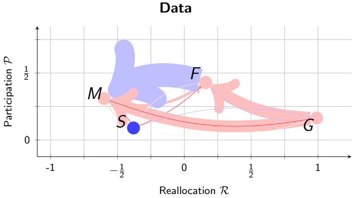
Distributions of loan rates between pairs of bank types



- Sample period: 2019/06/06–2019/07/31; ONRRP = 2.25%; IOR = 2.35%; EFFR = 2.39%; DWR = 3.0%
- The curve labeled i gives the fraction of total reserves borrowed by banks of type i from the bank type indicated in the panel heading, at rates lower than a given rate

Fed funds trading network (2019)





Aggregate Demand for Reserves

(Theory)

Counterfactuals for the supply of reserves (Q)

details

- When the Fed drains \$1 bn in reserves, how does the distribution of reserves change across banks?

$$Q \equiv \sum_{i \in \mathbb{N}} n_i \int a dF_0^i(a)$$

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Our approach

Vary the distribution $\{F_0^i, n_i\}_{i \in \mathbb{N}}$ along "quantile interpolations" of the estimated empirical distribution at two endpoints

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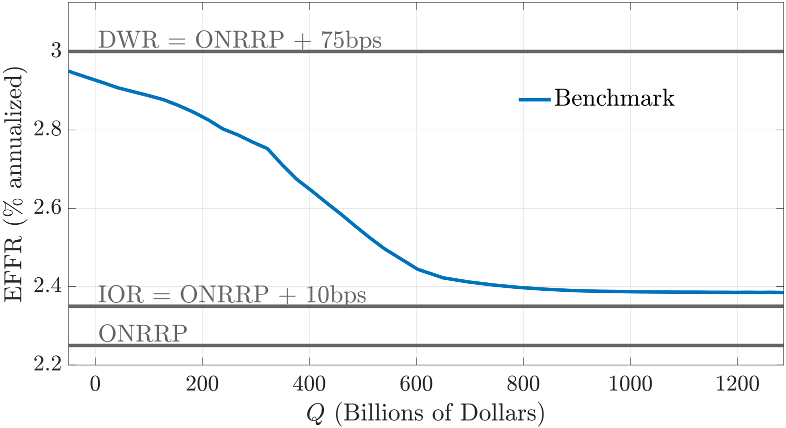
Vary the distribution $\{F_0^i, n_i\}_{i \in \mathbb{N}}$ along "quantile interpolations" of the estimated empirical distribution at two endpoints

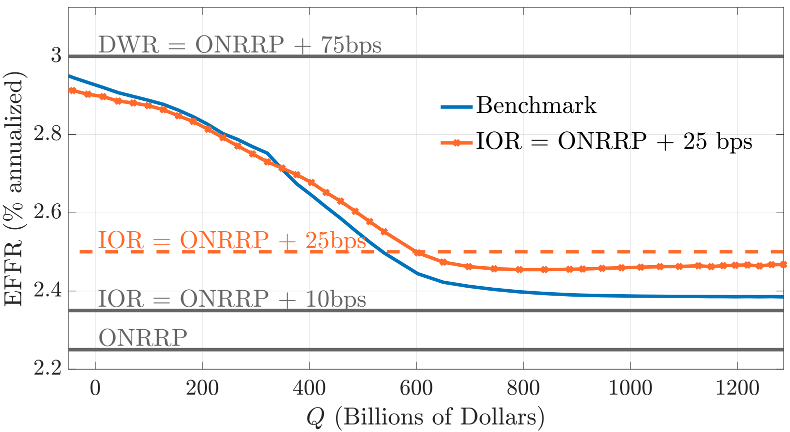
- Estimate distributions $\{F_0^i, n_i\}_{i \in \mathbb{N}}$ for years 2017 and 2019.
- Compute "interpolations" $\{\bar{F}_\omega^i, n_\omega\}_{i \in \mathbb{N}}$ for a range of $\omega \in \mathbb{W} \subset \mathbb{R}$
- Each ω implies: reserves Q_ω and a fed-funds rate ι_ω^*

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: IOR-ONRRP spread



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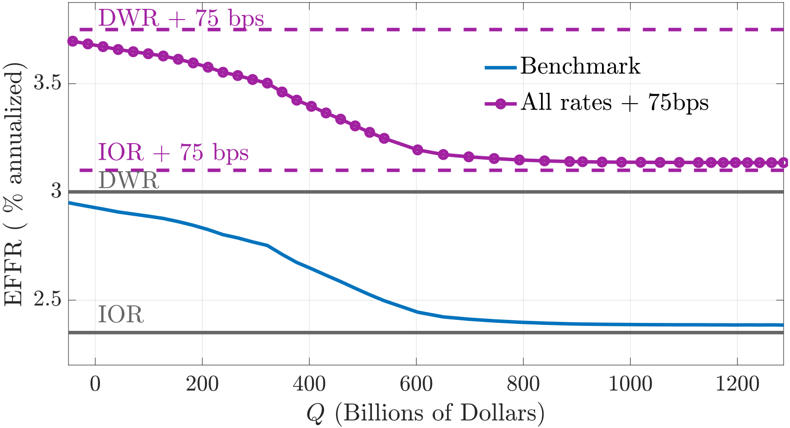
Counterfactual: corridor shift



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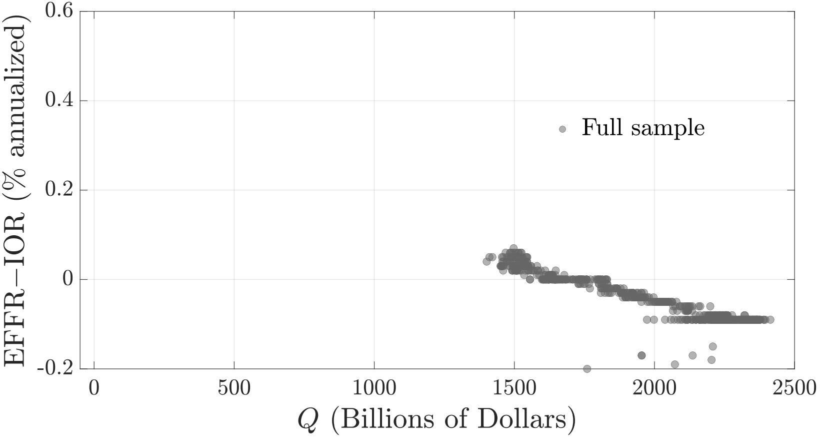
Aggregate Demand for Reserves

(Estimation)

Curve fitting with no theory



- Full sample: 2017/01/20–2019/09/13

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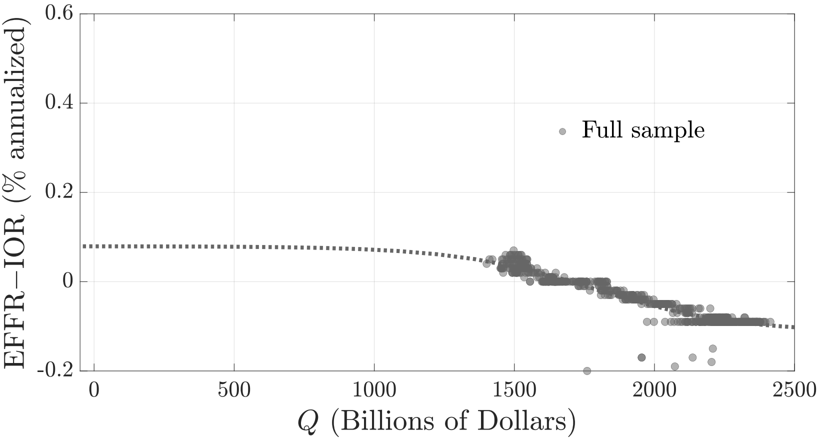
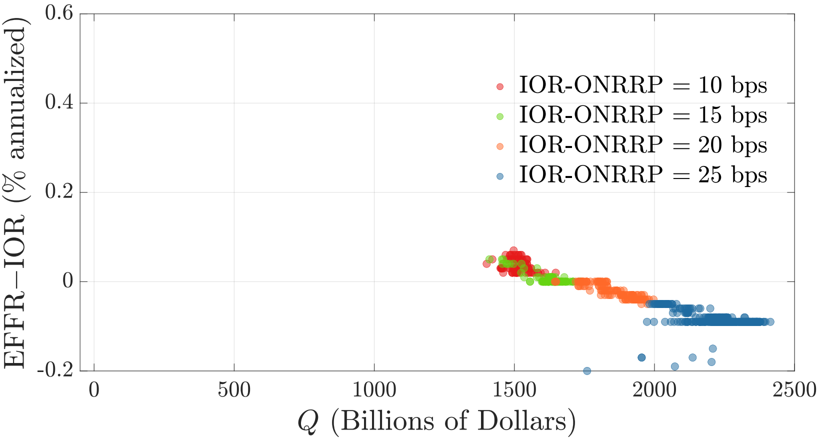


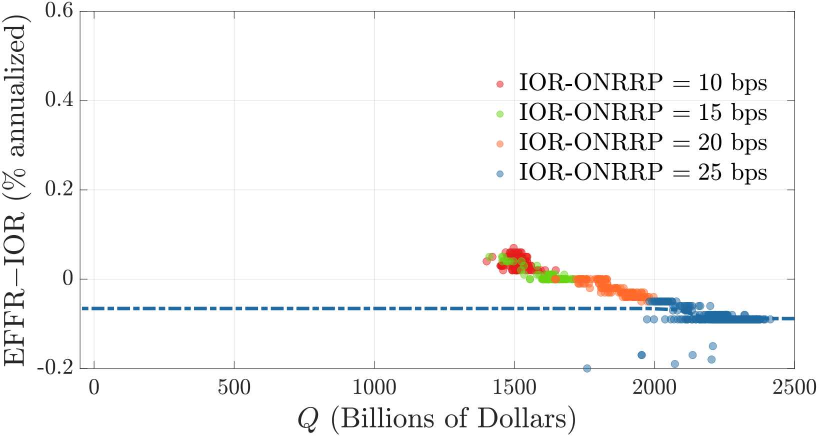
- Full sample: 2017/01/20–2019/09/13
- NLS fit of $s_t = D(Q_t)$ with $D(Q_t) \equiv \underline{s} + \frac{\bar{s}-\underline{s}}{1+e^{(Q_t - Q_0)\xi}}$

Curve fitting with a bit of theory



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

Curve fitting with a bit of theory



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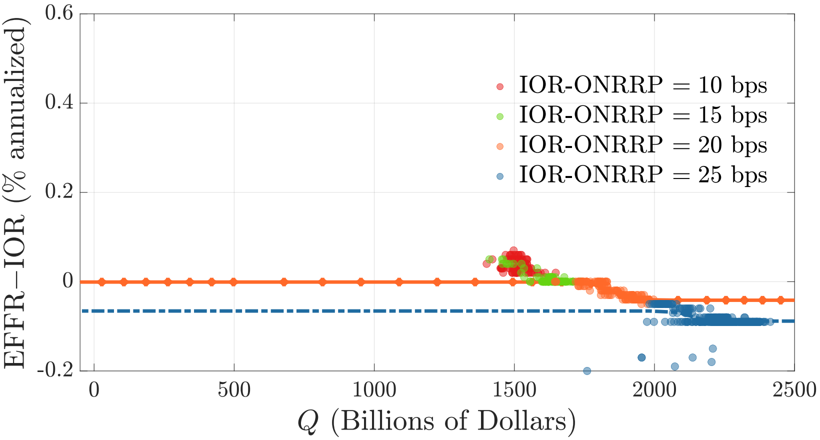

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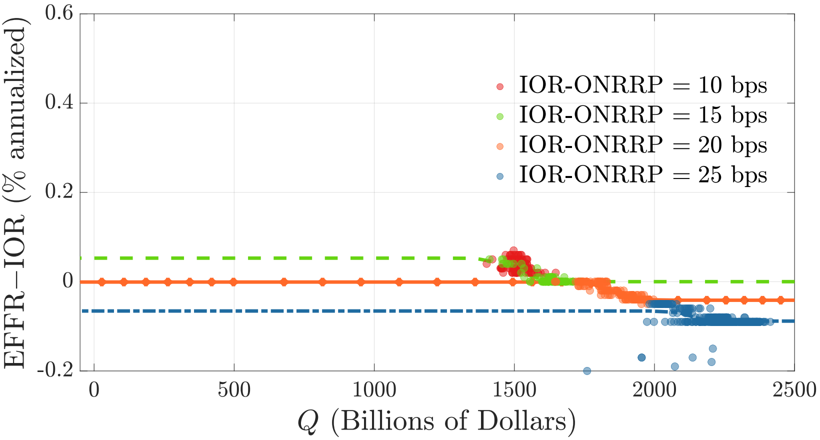

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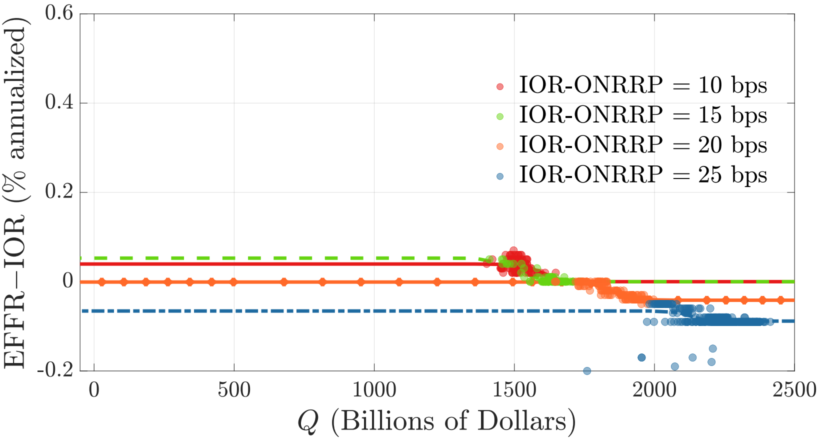

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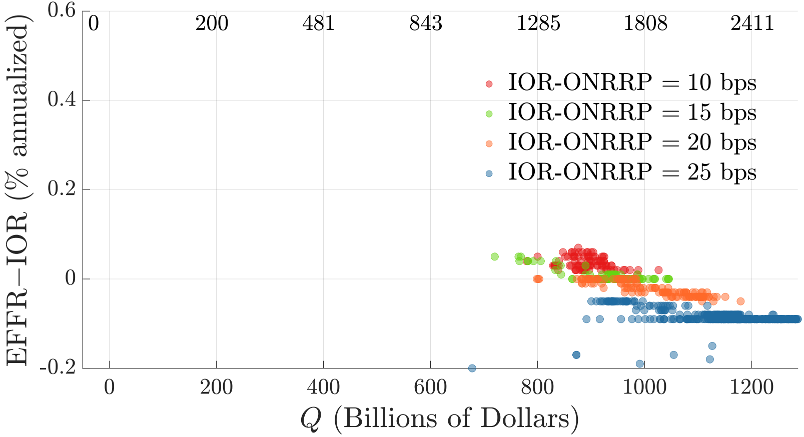
Quantitative-theoretic estimation



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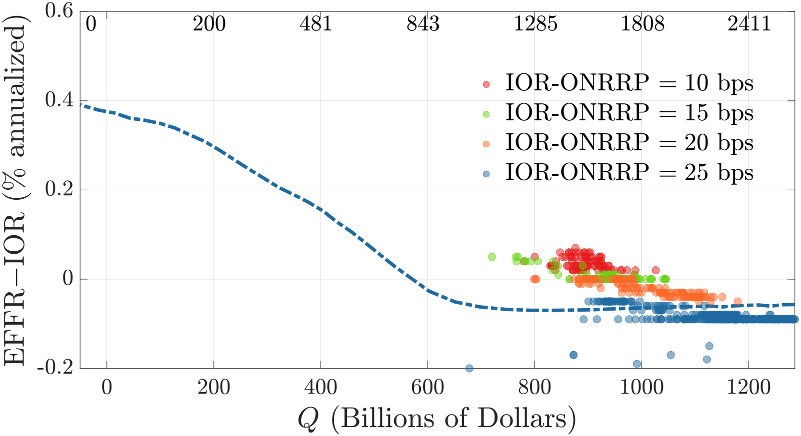

- Sample 2017/01/20–2019/09/13 split by IOR-ONRRP regime
- ADR implied by the theory (baseline calibration, but with administered rates to match the subsample)

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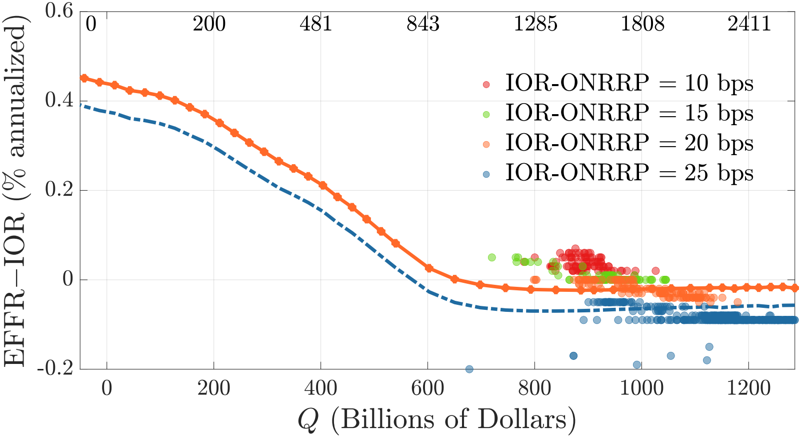

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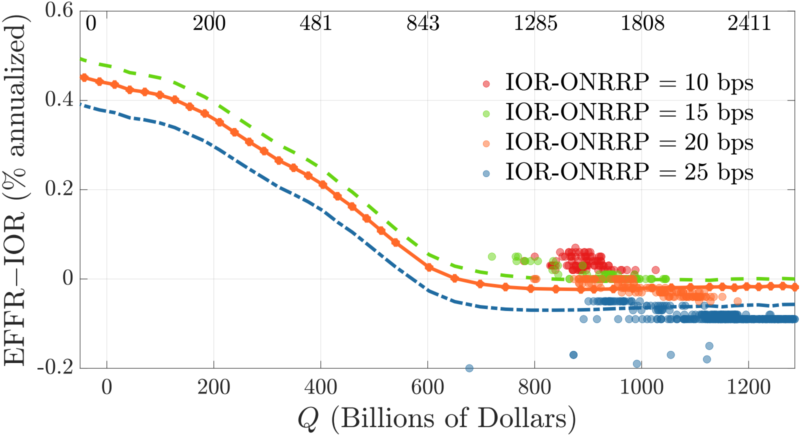

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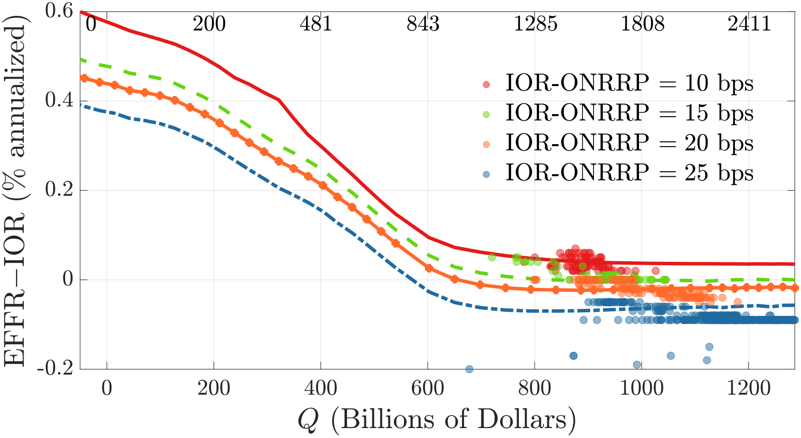

- Sample 2017/01/20–2019/09/13 split by IOR-ONRRP regime
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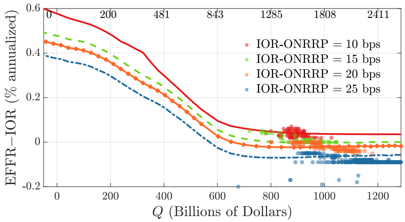
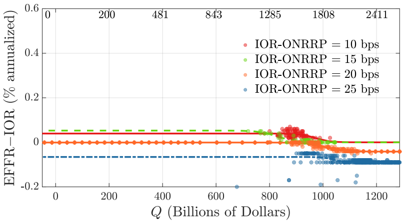
Quantitative-theoretic estimation vs. NLS fit

Theoretical demand under baseline calibration



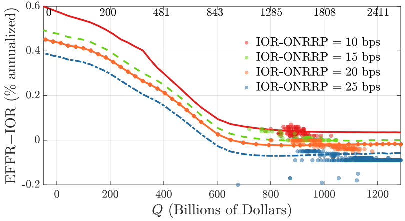
NLS fit of $s_t = D(Q_t) \equiv \underline{s} + \frac{\bar{s}-\underline{s}}{1+e^{(Q_t-Q_0)\xi}}$



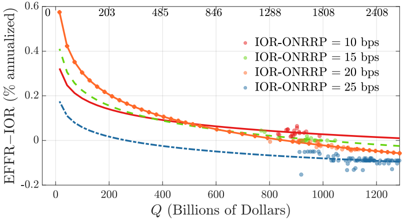
- Sample period: 2017/01/20–2019/09/13 split by IOR-ONRRP regime

Quantitative-theoretic estimation vs. LS-VJ OLS fit

Theoretical demand under baseline calibration



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

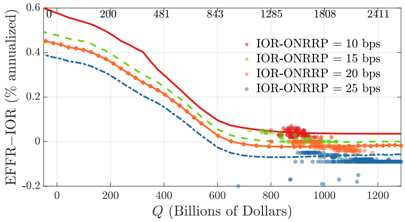


- Sample period: 2017/01/20–2019/09/13 split by IOR-ONRRP regime

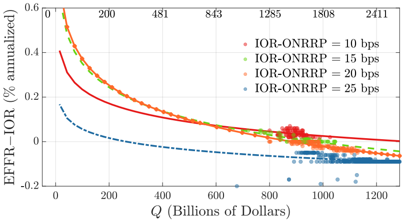
Quantitative-theoretic estimation vs. semi-log OLS fit

more

Theoretical demand under baseline calibration



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



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

Curve fitting exercises – summary

- Reasonable empirical models deliver different ADR estimates
  - $\rightarrow$ *local* to *global* estimates ...
- Our theoretical model delivers reasonable global ADR estimate
  - $+$ Performs well for several IOR-ONRRP values (not targeted!)
  - $+$ Useful for policy analysis/counterfactuals

Navigational Tools

Monetary Confidence Band

- Fed does not have *complete control* over the supply of reserves
- Supply of reserves is largely controlled by the Fed, but also depends on transactions in which the Fed is not a counterparty (e.g.: TGA)

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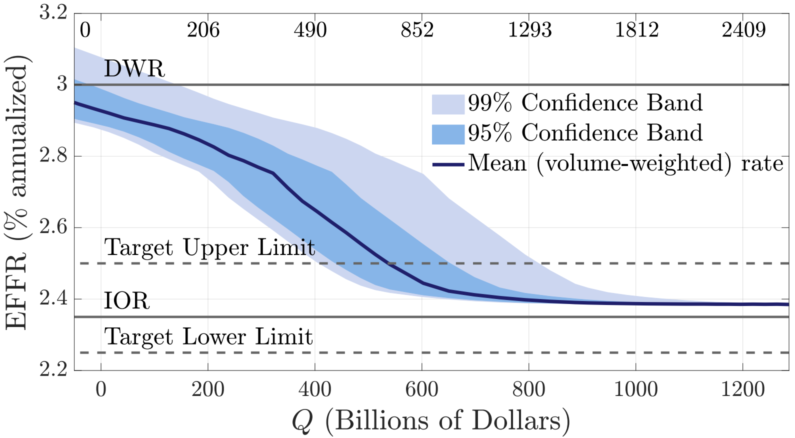
Objective

Monetary Confidence Band Estimate distribution of daily "exogenous" reserve-draining shocks and incorporate uncertainty to model predictions.

Monetary Confidence Band

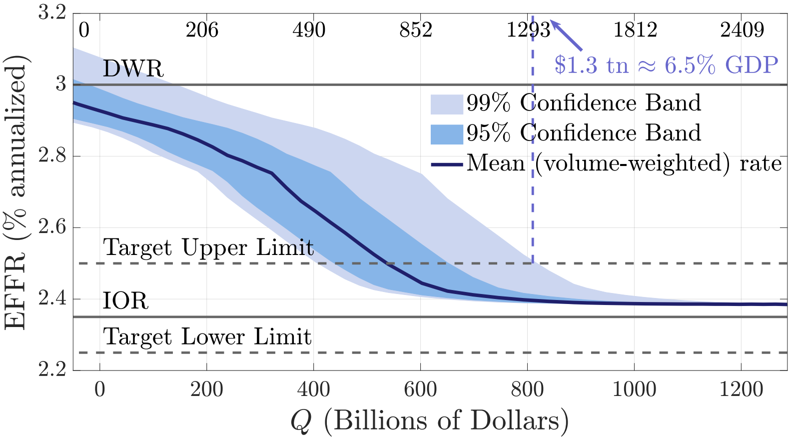
more $\mu(a)_i$



- 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%

Monetary Confidence Band

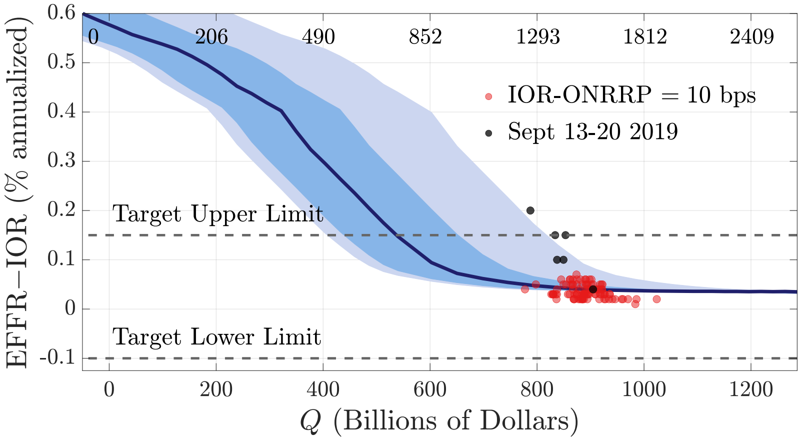
more $\mu(a)_i$



- 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%

September 17, 2019

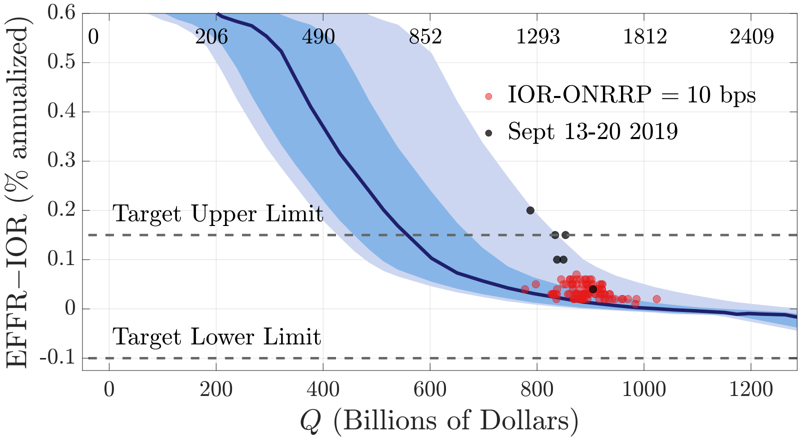
The money-market events of September 17, 2019



- 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)

September 17, 2019 when F don't trade

red line?



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

Conclusion

Summary

- Developed prototypical model of the fed funds market (Afonso and Lagos (2015)) by incorporating bank-level heterogeneity in:
  - payoffs
  - degree of centrality in market-making
  - frequency and size distributions of payment shocks
- Documented new micro-level and marketwide facts
- Showed the heterogeneous-bank OTC theory can match the facts
- Used the quantitative theory to:
  - estimate the aggregate demand for reserves in the United States
  - develop "navigational tools" for policy implementation (e.g., MCBs)

Summary and future work

- Developed prototypical model of the fed funds market (Afonso and Lagos (2015)) by incorporating bank-level heterogeneity in:
  - payoffs
  - degree of centrality in market-making
  - frequency and size distributions of payment shocks
- Documented new micro-level and marketwide facts
- Showed the heterogeneous-bank OTC theory can match the facts
- Used the quantitative theory to:
  - estimate the aggregate demand for reserves in the United States
  - develop "navigational tools" for policy implementation (e.g., MCBs)
- For future applications, it may be useful to:
  - endogenize frequency of trade (e.g., bank's search intensity)
  - endogenize BOD distributions (bank's portfolio choices)
  - explore macro implications of microstructure of money markets (e.g., through bank lending decisions)

scan to find the paper

Appendix

Bargaining outcomes

$$\max_{b,R}\left[V_t^i\left(a_i-b\right)+e^{-r(\bar{T}-t)}R-V_t^i\left(a_i\right)\right]^{\theta_{ij}}\left[V_t^j\left(a_j+b\right)-e^{-r(\bar{T}-t)}R-V_t^j\left(a_j\right)\right]^{\theta_{ji}}$$

- b and R outcomes of Nash bargaining
- θ_{ij} bargaining power, repayment at $\bar{T}>T$
- $V_t^i(\cdot)$ encodes potential future trades
- banks distribution matters!

Bargaining outcomes

$$\max_{b,R}\left[V_t^i\left(a_i-b\right)+e^{-r(\bar{T}-t)}R-V_t^i\left(a_i\right)\right]^{\theta_{ij}}\left[V_t^j\left(a_j+b\right)-e^{-r(\bar{T}-t)}R-V_t^j\left(a_j\right)\right]^{\theta_{ji}}$$

- b and R outcomes of Nash bargaining
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- $V_t^i(\cdot)$ encodes potential future trades
- banks distribution matters!

Bilateral interest rates

$$1+\rho_t^{ji}\left(a_j,a_i\right)\equiv\frac{R_t^{ji}\left(a_j,a_i\right)}{b_t^{ij}\left(a_i,a_j\right)}$$

Value functions

$$V_T^i(a) = U_i(a)$$

$$\begin{aligned} rV_t^i(a) &= \dot{V}_t^i(a) + u_i(a) \\ &\quad + \beta_i \sum_{j \in \mathbb{N}} \frac{\beta_j n_j}{\sum_{k \in \mathbb{N}} \beta_k n_k} \theta_{ij} \int \max_{b \in \bar{\mathbb{R}}} S_t^{ij}(a, \tilde{a}, b)\, dF_t^j(\tilde{a}) \\ &\quad + \lambda_i \sum_{j \in \mathbb{N}} \frac{\lambda_j n_j}{\sum_{i \in \mathbb{N}} \lambda_i n_i} \int \left[V_t^i(a - z) - V_t^i(a) \right] dG_{ij}(z) \end{aligned}$$

$$S_t^{ij}(a, \tilde{a}, b) \equiv V_t^i(a - b) + V_t^j(\tilde{a} + b) - V_t^i(a) - V_t^j(\tilde{a})$$

Laws of motion for the distributions of balances

$$
\begin{aligned}
\dot{f}_t^i(a) = & -(\beta_i + \lambda_i) f_t^i(a) \\
& + \beta_i \sum_{j \in \mathbb{N}} \frac{\beta_j n_j}{\sum_{k \in \mathbb{N}} \beta_k n_k} \int \int \mathbb{I}_{\{a_i - b_t^{ij}(a_i, a_j) = a\}} f_t^j(a_j) f_t^i(a_i) \\
& + \lambda_i \sum_{j \in \mathbb{N}} \frac{\lambda_j n_j}{\sum_{i \in \mathbb{N}} \lambda_i n_i} \int \int \mathbb{I}_{\{a_i - z = a\}} dG_{ij}(z) f_t^i(a_i)
\end{aligned}
$$

where $f_t^i \equiv dF_t^i$, and f_0^i is given

Equilibrium

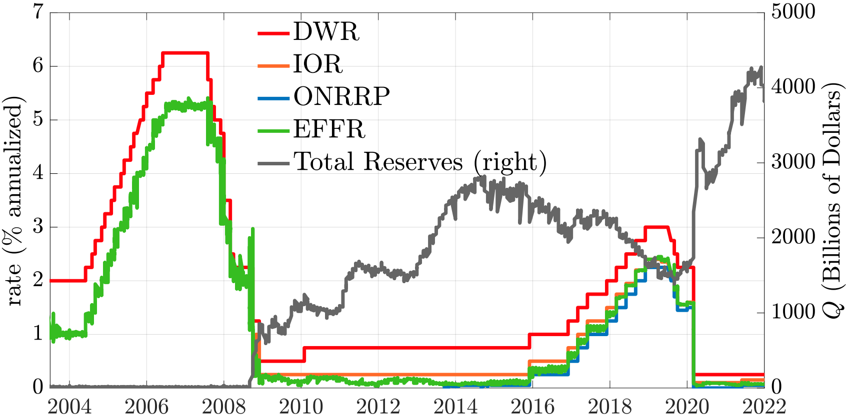
An equilibrium is a time-path

$$\left\{ \left\{ b_t^{ij}\left(\cdot,\cdot\right), R_t^{ij}\left(\cdot,\cdot\right), V_t^{i}\left(\cdot\right), F_t^{i}\left(\cdot\right) \right\}_{i,j\in\mathbb{N}} \right\}_{t\in\mathbb{T}}$$

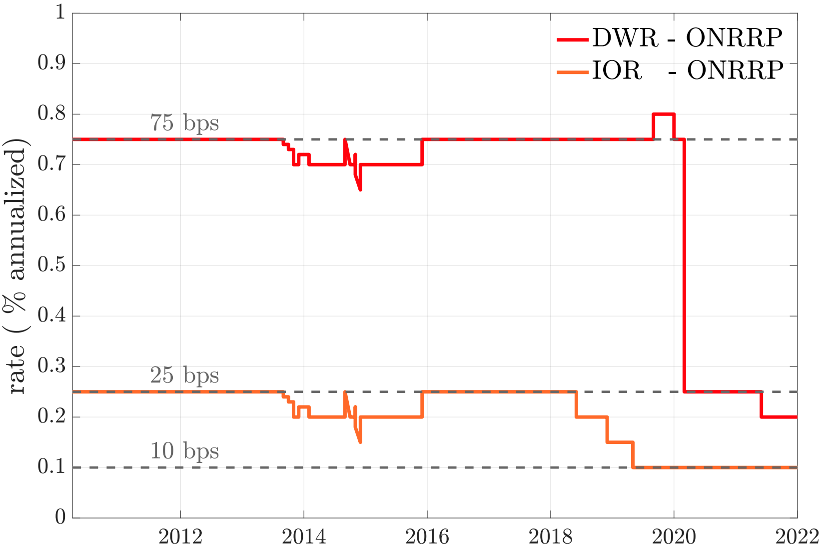
that satisfies:

- Bargaining outcomes
- Bellman equations
- Laws of motion for the distributions of balances

Reserves, administered rates, and EFFR



Administered spreads: DWR-ONRRP, IOR-ONRRP



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	GSE	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)

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

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

- $\mathcal{P}_{ih} = \sum_{m \in i} \frac{\upsilon^e_{mh} + \upsilon^r_{mh}}{\upsilon_h}$: 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 $i \in \{F, M, S, GSE\}$

- $\mathcal{R}_{ih} = \frac{\sum_{m \in i} \upsilon^e_{mh} - \sum_{m \in i} \upsilon^r_{mh}}{\sum_{m \in i} \upsilon^e_{mh} + \sum_{m \in i} \upsilon^r_{mh}}$: 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 $i \in \{F, M, S, GSE\}$
- 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

Payments

estimation

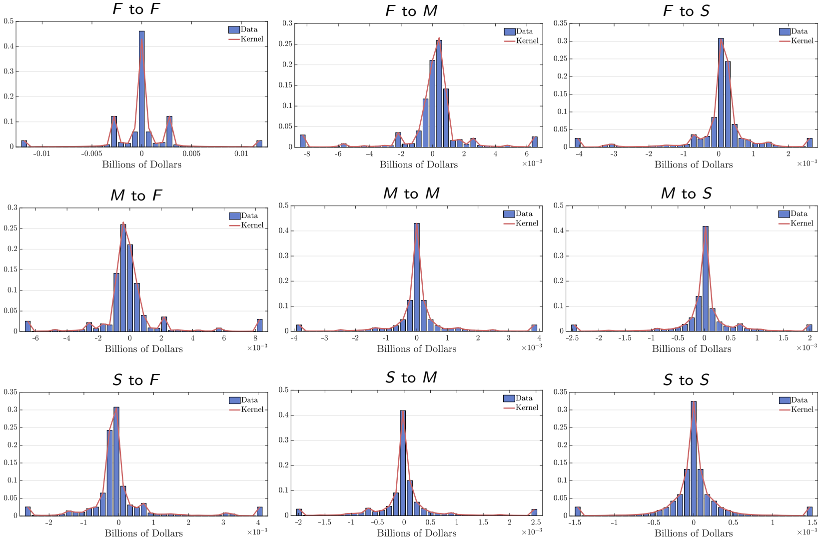
Objective

Use bank-level second-by-second payments data to:

- Split each payment into an *average component* and a *payment shock*
- Estimate empirical counterparts of theoretical payment-shock process:
  - λ_i : frequency of shocks for a typical bank of type i
  - G_{ij}: size distribution of shocks between pair of banks of types i, j

Size distributions of payment shocks (2019)

year 2006



Beginning-of-day distribution of reserves

Objective

Estimate empirical counterparts of beginning-of-day distributions $\{F_0^i\}_{i\in\mathbb{N}}$

Beginning-of-day distribution of reserves

calculations

Start with bank-level beginning-of-day *raw* reserves, and net out:

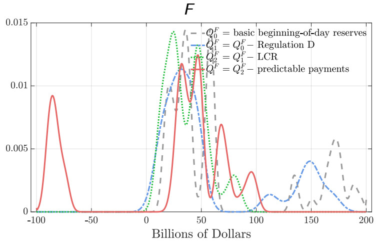
- Previous-day loan repayments
- Predictable payments (unrelated to loans)
- Regulation D and (imputed) LCR requirement

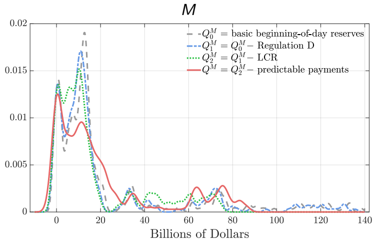
⇒ bank-level beginning-of-day *unencumbered reserves*

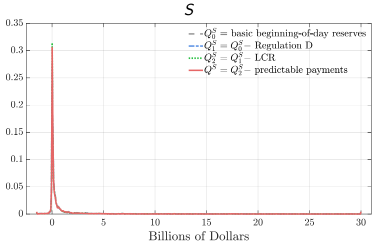
(relevant notion of beginning-of-day reserves in the theory)

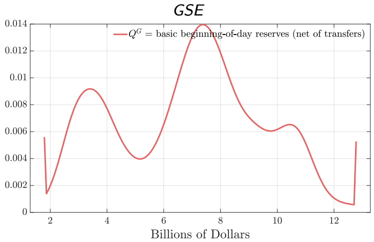
Beginning-of-day distributions of reserves (2019)

other years









Reserve-draining shocks

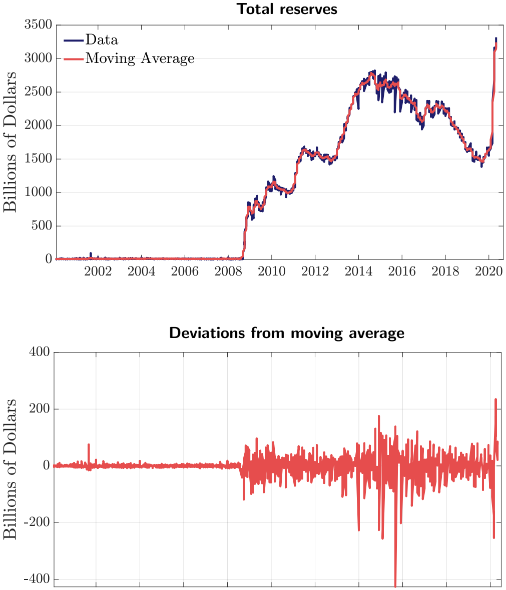
examples

- Fed does not have *complete control* over the supply of reserves
- Supply of reserves is largely controlled by the Fed, but also depends on transactions in which the Fed is not a counterparty (e.g.: TGA)

Objective

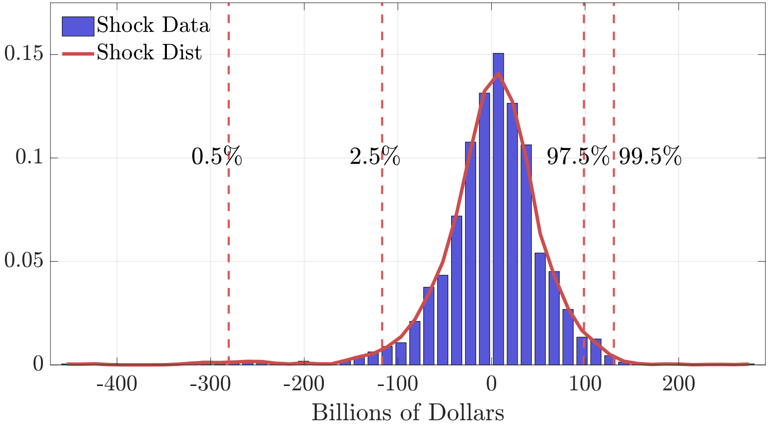
Estimate distribution of daily "exogenous" reserve-draining shocks

Reserve-draining shocks



Estimated distribution of reserve-draining shocks

estimation



Liquidity effect

- Fed does not have *complete control* over the supply of reserves
- Supply of reserves is largely controlled by the Fed, but also depends on transactions in which the Fed is not a counterparty (e.g.: TGA)

Objective

Estimate fed funds rate response to “exogenous” changes in supply of reserves

Liquidity effect: estimation

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)

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 $[-0.0187, -0.0052]$

Interbank payments: estimation

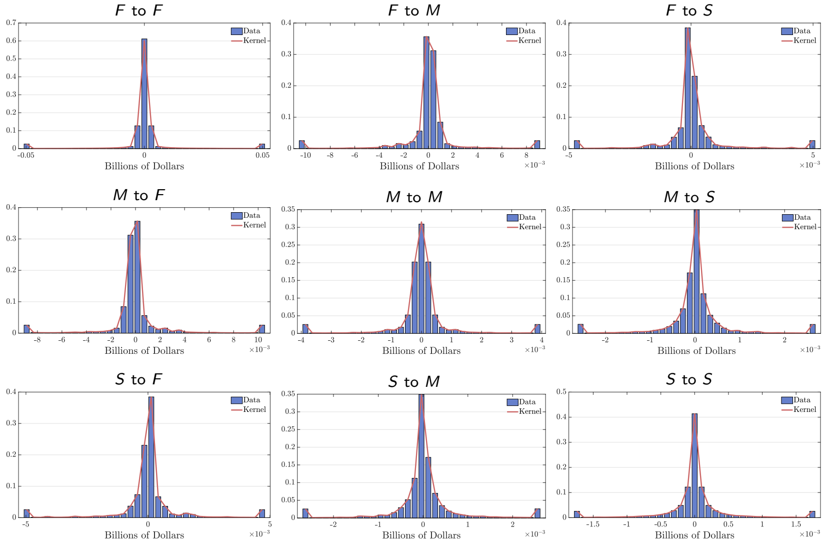
- $\mathbb{B}$: set of all banks
- $\mathbb{B}_i$: set of banks of type i
- N_i : number of banks of type i
- $\mathrm{s}_{mn}(t,d)$: value payments from bank m to bank n, in second t of day d
- $\bar{\mathrm{s}}_{mn}$: time-average of $\mathrm{s}_{mn}(t,d)$
- $\tilde{\mathrm{s}}_{mn}(t,d) \equiv \mathrm{s}_{mn}(t,d) - \bar{\mathrm{s}}_{mn}$: *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?

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Problem

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

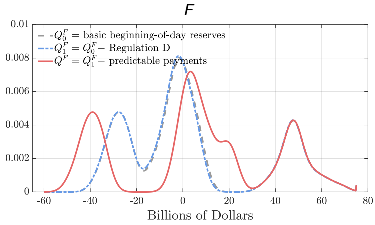
Our approach

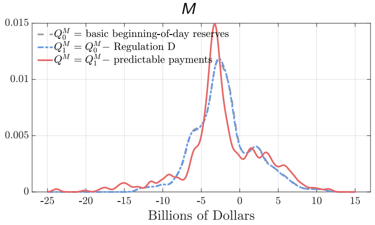
LCR-required reserves = smallest quantity of reserves needed to meet LCR:

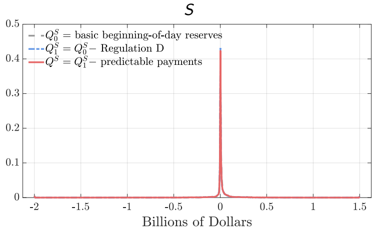
- $\mathrm{A}_{mh} \equiv \mathrm{H}_{mh} - \max\left(0, \mathrm{a}_{mh} - \underline{\mathrm{a}}^{D}_{mh}\right)$

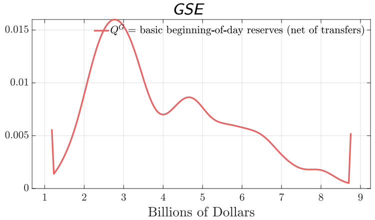
  qualifying HQLA *other than* reserves (a_{mh}) in excess of Regulation-D requirement ($\underline{\mathrm{a}}^{D}_{mh}$)
- $\underline{\mathrm{a}}^{L}_{mh} = \max\left(0, \mathrm{L}_{mh} - \mathrm{A}_{mh}\right)$ → our measure of *LCR-required reserves*
- $\mathrm{x}_{mh} \equiv \mathrm{a}_{mh} - \underline{\mathrm{a}}^{D}_{mh} - \underline{\mathrm{a}}^{L}_{mh}$ → our comprehensive measure of *excess reserves*

Beginning-of-day distributions of reserves (2006)

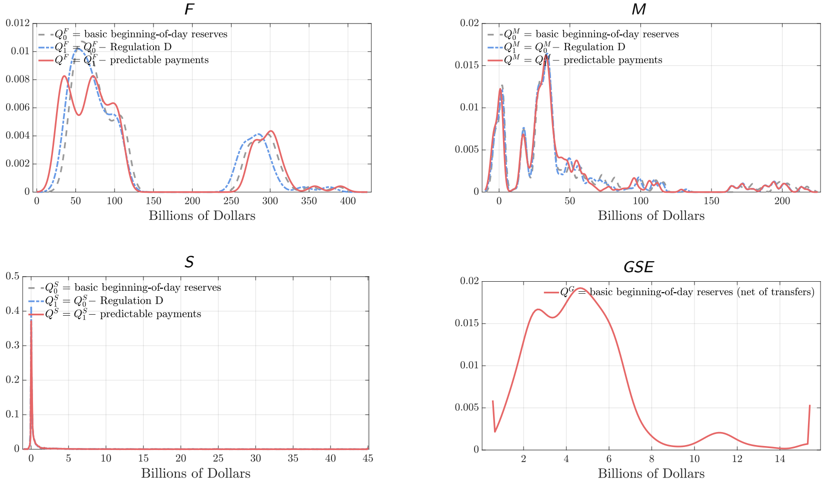




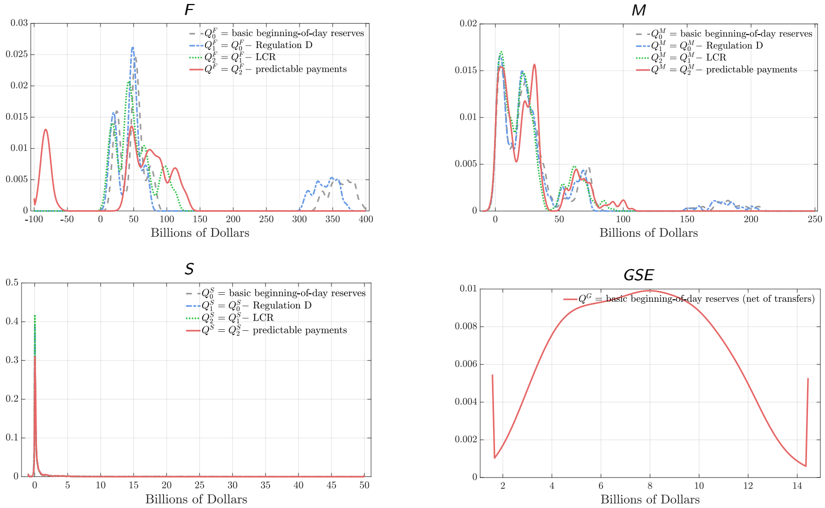




Beginning-of-day distributions of reserves (2014)



Beginning-of-day distributions of reserves (2017)



Reserve-draining shocks: 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: 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:

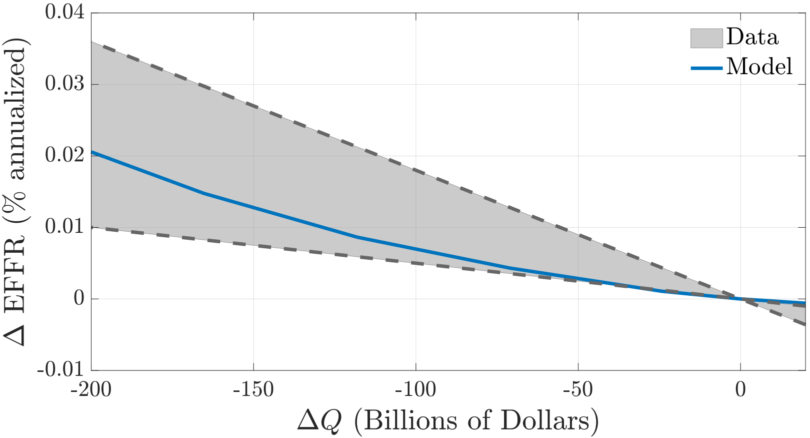
  2019/05/02–2019/09/13: DWR-ONRRP = 75 bps and IOR-ONRRP = 10 bps

  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

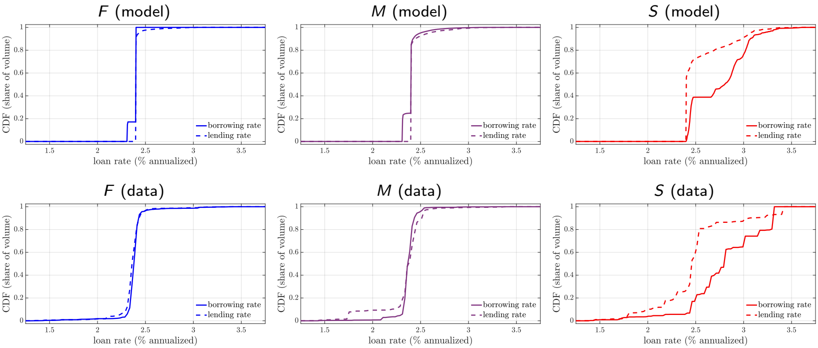


Conditional distribution of rates in excess of DWR

Loan rate statistics (conditional $\geq$ DWR)	Data	Model
10^{th} percentile	3.0%	3.0%
mean	3.1%	3.1%
90^{th} percentile	3.3%	3.3%
maximum	3.5%	3.8%

- Sample period: 2019/06/06–2019/07/31; ONRRP = 2.25%; IOR = 2.35%; EFFR = 2.39%; DWR = 3.0%

Bid-ask spread by bank type



- Sample period: 2019/06/06–2019/07/31; ONRRP = 2.25%; IOR = 2.35%; EFFR = 2.39%; DWR = 3.0%

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

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☞ relevant measure of aggregate reserves for the theory

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- *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

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	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

Counterfactuals for Q: our approach

calibration

- Estimate BOD distributions $\left\{\bar{F}^i_{\mathrm{Y}_0}, \bar{F}^i_{\mathrm{Y}_1}\right\}_{i\in\mathbb{N}}$ 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:

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

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

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 $\left(Q_{\mathrm{Y}_\omega}\right)$ by varying ω

Aggregate demand for reserves in the theory

- Estimate BOD distributions $\left\{\bar{F}^i_{\mathrm{Y}_0}, n^i_{\mathrm{Y}_0}, \bar{F}^i_{\mathrm{Y}_1}, n^i_{\mathrm{Y}_1}\right\}_{i\in\mathbb{N}}$
- Compute "interpolations" $\left\{\bar{F}^i_{\mathrm{Y}_\omega}, n_{\mathrm{Y}_\omega}\right\}_{i\in\mathbb{N}}$ for a range of $\omega \in \mathbb{W} \subset \mathbb{R}$
- Each ω implies
  - a supply of reserves, $Q_{\mathrm{Y}_\omega} \equiv \sum_{i\in\mathbb{N}} \bar{n}^i_{\mathrm{Y}_\omega} \int a d\bar{F}^i_{\mathrm{Y}_\omega}(a)$, and
  - a volume-weighted average of all equilibrium bilateral loan rates, $\iota^*_{\mathrm{Y}_\omega}$
- Varying $\omega \in \mathbb{W} \Rightarrow$ negative relationship between Q_{Y_ω} and $\iota^*_{\mathrm{Y}_\omega}$

Aggregate demand for reserves in the theory

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The schedule of equilibrium pairs, $\{(Q_{\mathrm{Y}_\omega}, \iota^*_{\mathrm{Y}_\omega})\}_{\omega\in\mathbb{W}}$, is the *"aggregate demand for reserves"* implied by the theory

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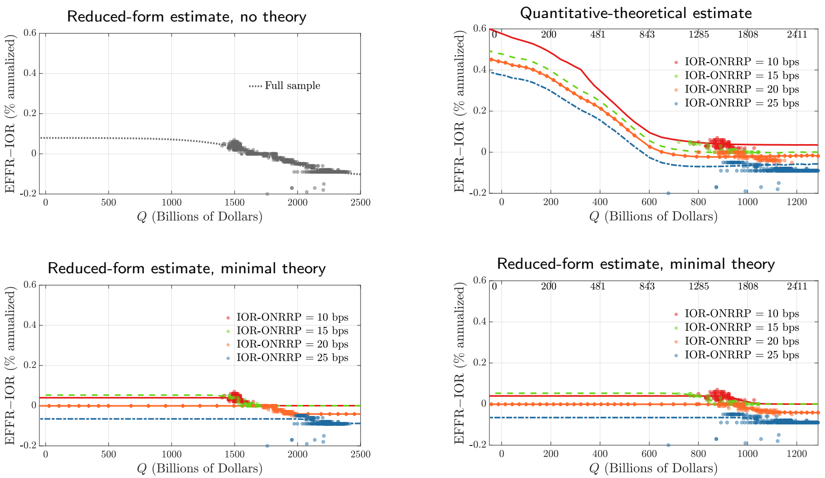
- The schedule of equilibrium pairs, $\{(Q_{Y_\omega}, \iota^*_{Y_\omega})\}_{\omega\in\mathbb{W}}$, is the *"aggregate demand for reserves"* implied by the theory

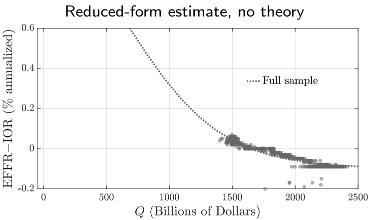
- We use $Y_0 = 2017$ and $Y_1 = 2019$

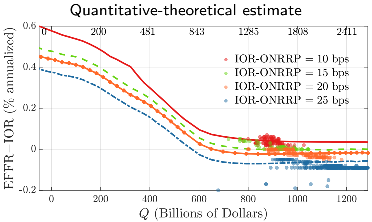
	Active Excess Reserves	Total Reserves
2017	\$1,150.86 bn	\$2,254.27 bn
2019	\$910.73 bn	\$1,568.27 bn

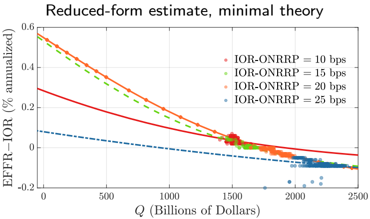
Estimation: model vs. $s_t = \underline{s} + \frac{\bar{s} - \underline{s}}{1 + e^{(Q_t - Q_0)\xi}}$

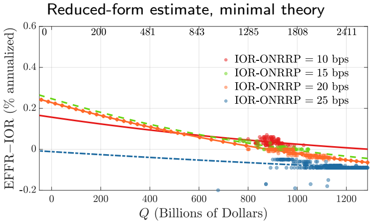


Estimation: model vs. $s_t = \underline{s} + \frac{\overline{s} - \underline{s}}{1 + e^{(Q_t - Q_0)\xi}}$ (version 2)

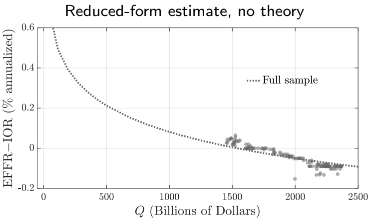


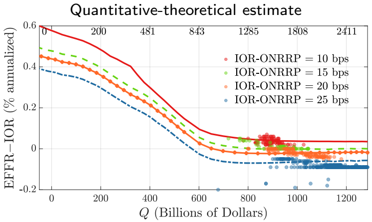


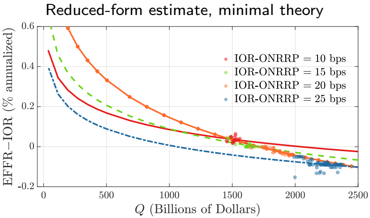


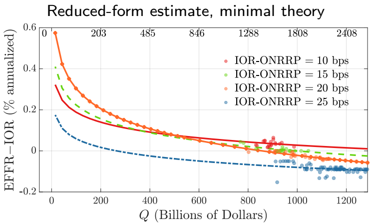


Estimation: model vs. $s_t = a + b\ln(Q_t) + c\ln(D_t)$



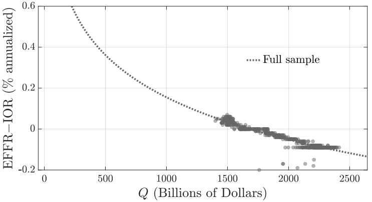




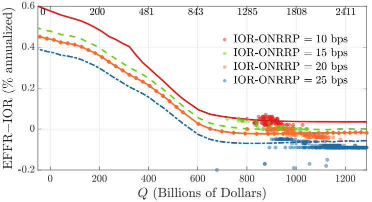


Estimation: model vs. $s_t = a + b \ln(Q_t)$

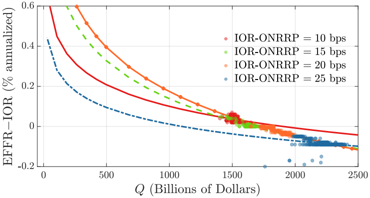
Reduced-form estimate, no theory



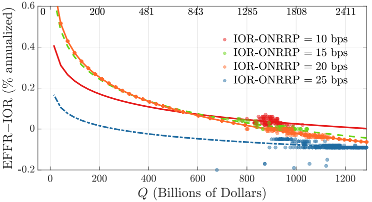
Quantitative-theoretical estimate



Reduced-form estimate, minimal theory

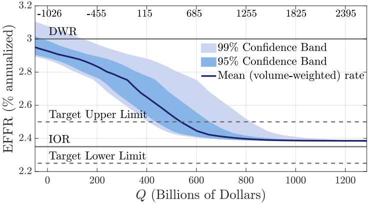


Reduced-form estimate, minimal theory

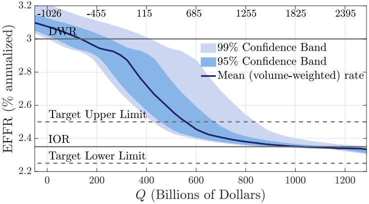


Monetary Confidence Banks: counterfactuals

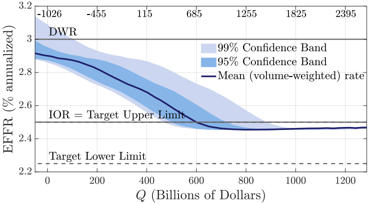
Baseline calibration



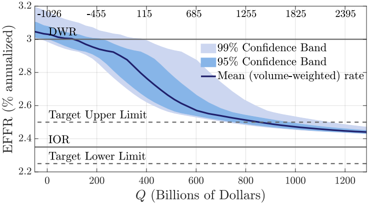
$\beta_F = 0$



IOR = ONRRP + 25 bps



Intraday overdraft penalty

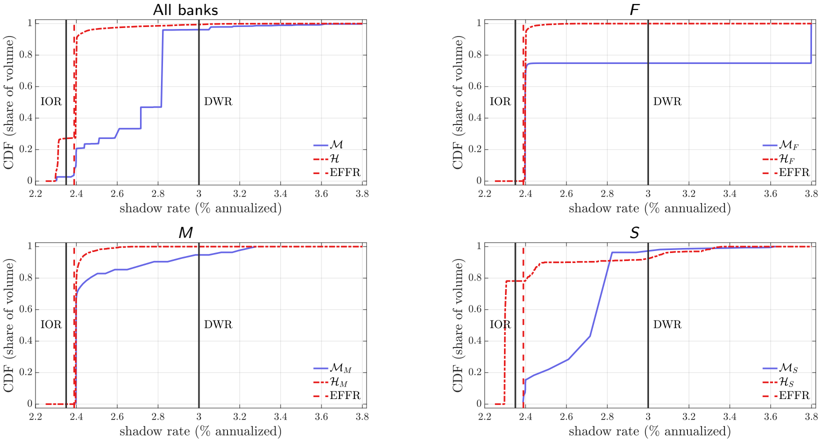


Shadow fed fund rates

$$\mu_i(a) \equiv \frac{\partial V_0^i(a)}{\partial a} - 1$$

$\mu_i(a)$ is the beginning-of-day marginal return from holding reserves for a bank of type i with reserve balance a

Distribution of shadow fed fund rates



- EFFR = equilibrium average (value-weighted) loan rate
- $\mathcal{H}$: CDF of all bilateral loans ($\mathcal{H}_i$ for loans negotiated by banks of type i)
- $\mathcal{M}$: BOD CDF of shadow rates for all banks ($\mathcal{M}_i$ for all banks of type i)

\$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

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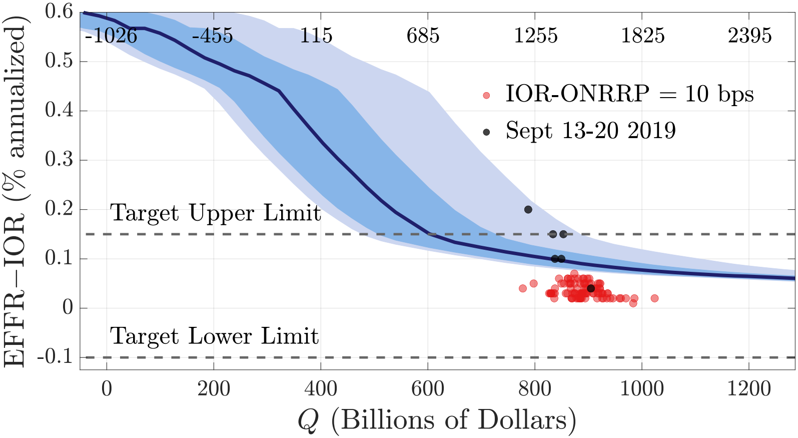
—Jamie Dimon, Chairman and CEO of JPMorgan Chase
October 15, 2019 earnings call

- add intraday overdraft cost: $u_i < 0$ if $a < 0$

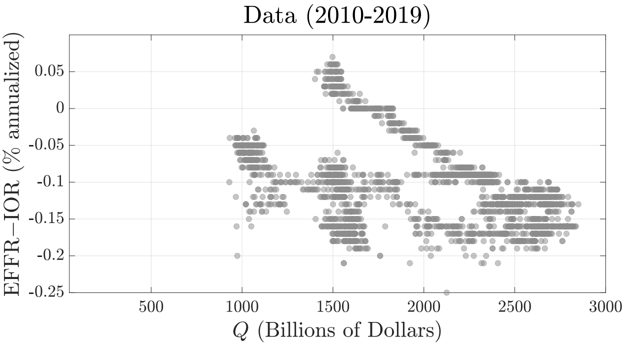
→ $u_i = (10\% \text{ of DWR}) \times (\text{time with } a < 0)$

2019/09/17: Jamie Dimon's "red line".

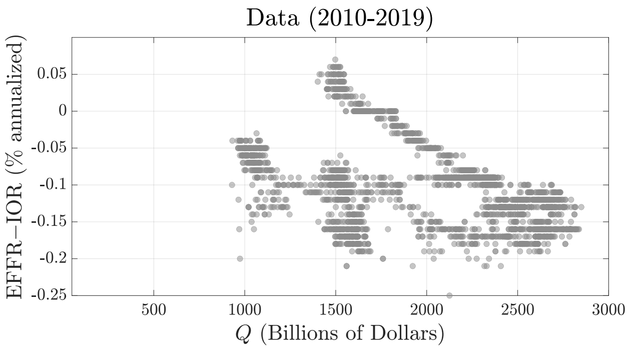


- Sample period: 2017/01/20–2019/09/13 ∪ 2019/09/16,17,18,19,20
- MCB for baseline calibration but with $u_i(a) = \iota_d a \mathbb{I}_{\{a<0\}}$ for all i; $\iota_d = \frac{x}{800}\iota_w$, and $x = 0.1$

Can you spot a “demand for reserves”?



Can you spot a "demand for reserves"?



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

$$\Rightarrow$$

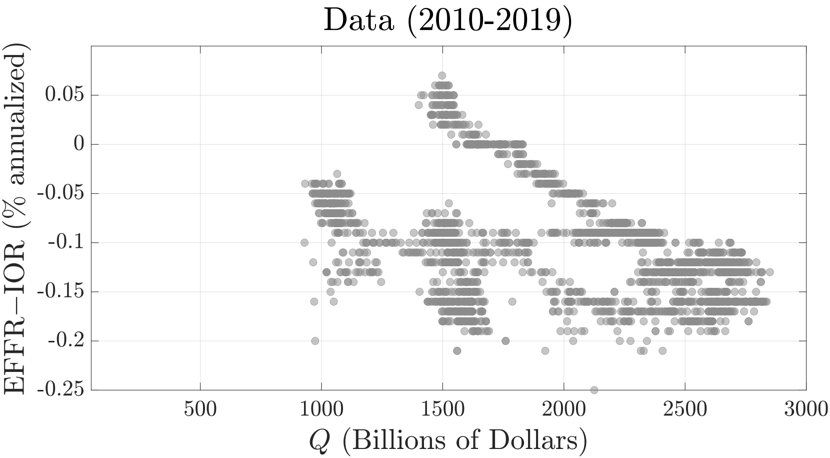
- Bad idea to simply run $EFFR - IOR = a + bf(Q)$ (e.g., $f(Q) = Q$, or $ln(Q)$)
- To identify "demand", need to control for structural factors behind these shifts

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 $\Rightarrow \left.\frac{d\ln(Q_t)}{d\ln(D_t)}\right|_{s_t=\bar{s}} = -\frac{c}{b} \approx 2.13$
  - $Q_{2019} = \$1.7tn$, $D_{2019} = \$13tn \Rightarrow \frac{0.0213\times 1.7}{0.01\times 13} \approx 0.28$

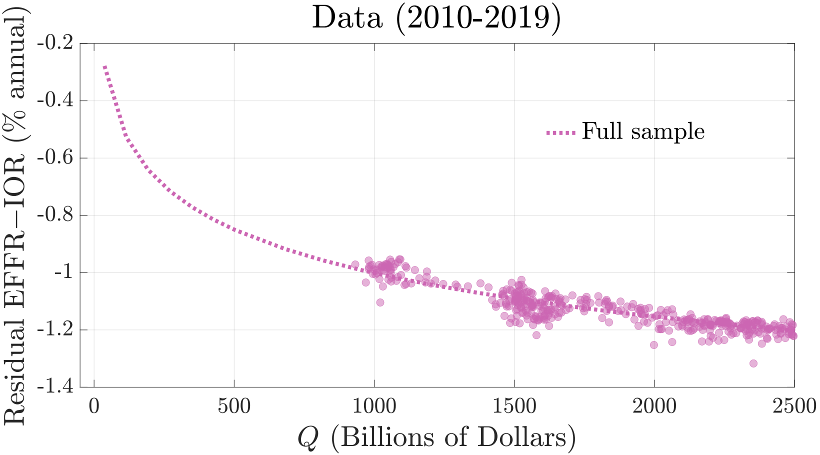
    $\Rightarrow$ 28 cents per dollar received in deposits is held as reserves to insure the idiosyncratic withdrawal risk of the deposit
  - Seems rather large...
    2000–2007: $Q_t/D_t < 0.01$ (above 0.2 for 2013–2016)
    ... maybe bulk of demand shift is not due to deposit growth?

What do we do about this?



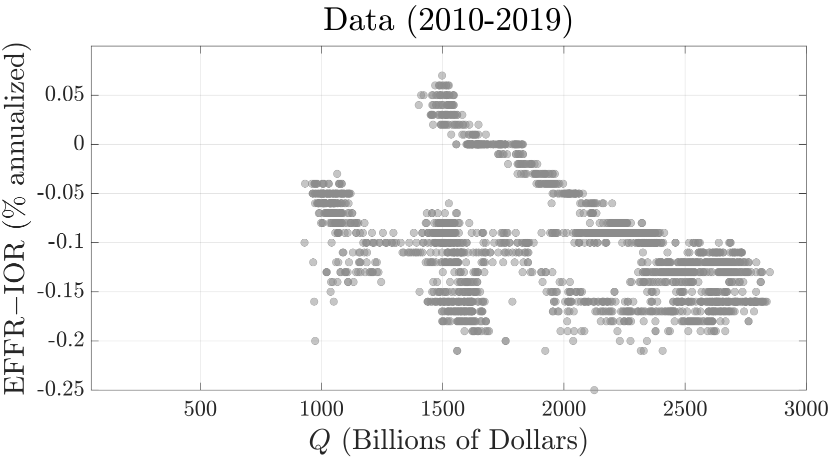
- 2010–2019, daily data

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



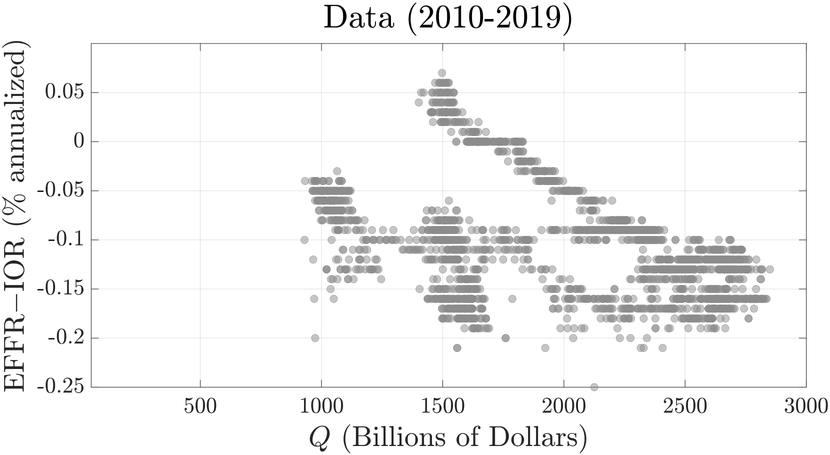
- 2010–2019, weekly data (D_t = demand deposits)
- OLS fit of $y_t \equiv s_t - a - b\ln(D_t)$ on Q_t

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



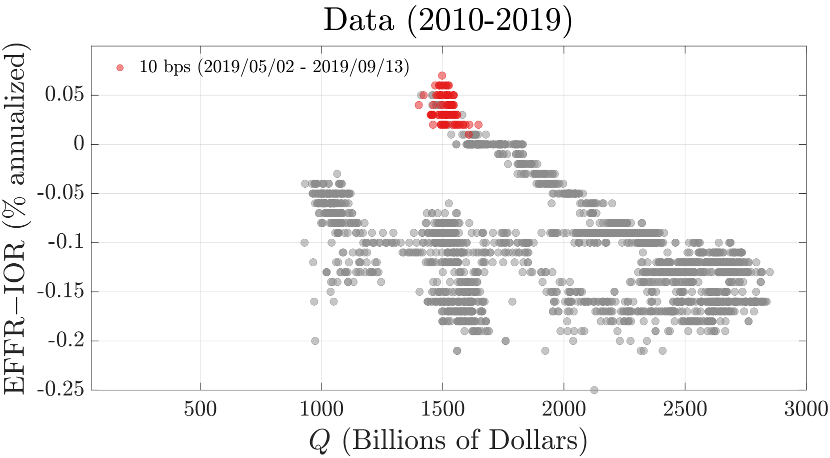
- 2010–2019, daily data

IOR-ONRRP as demand shifter



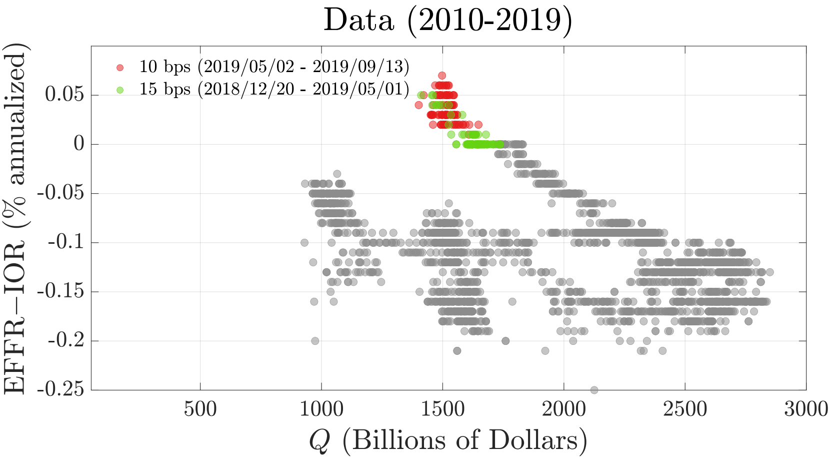
- 2010–2019, daily data

A bit of theory: identify IOR-ONRRP policy regimes



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

A bit of theory: identify IOR-ONRRP policy regimes



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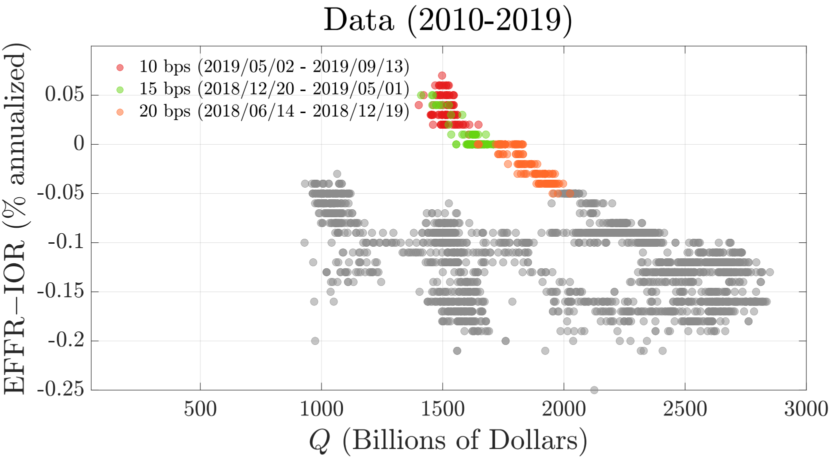

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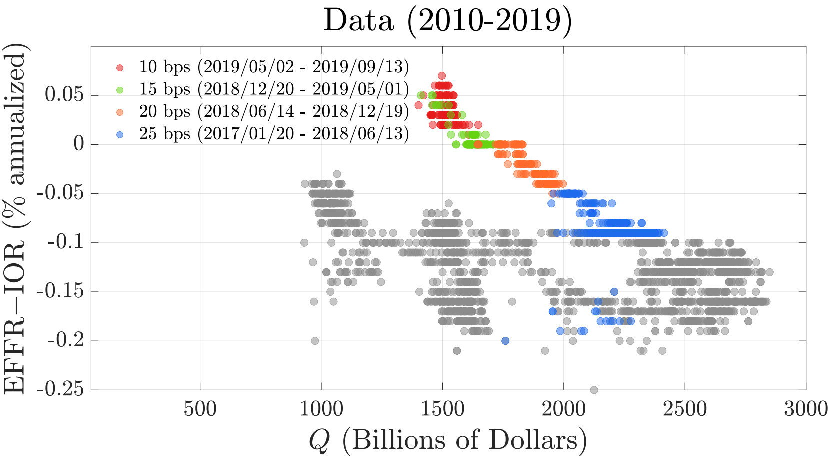

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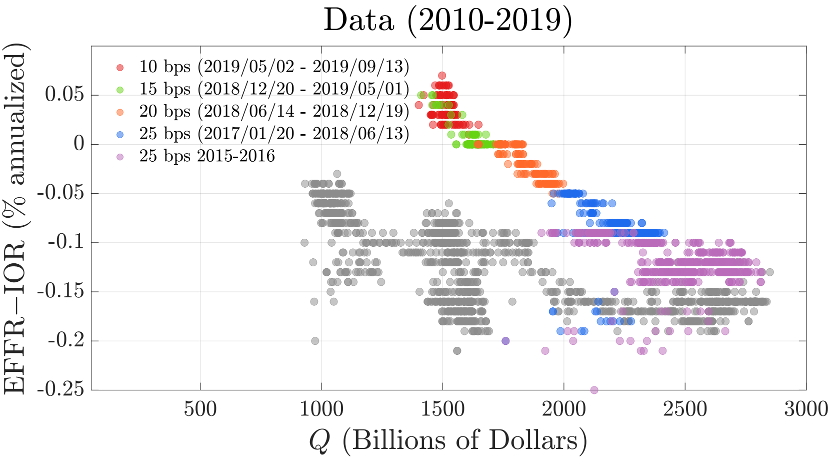

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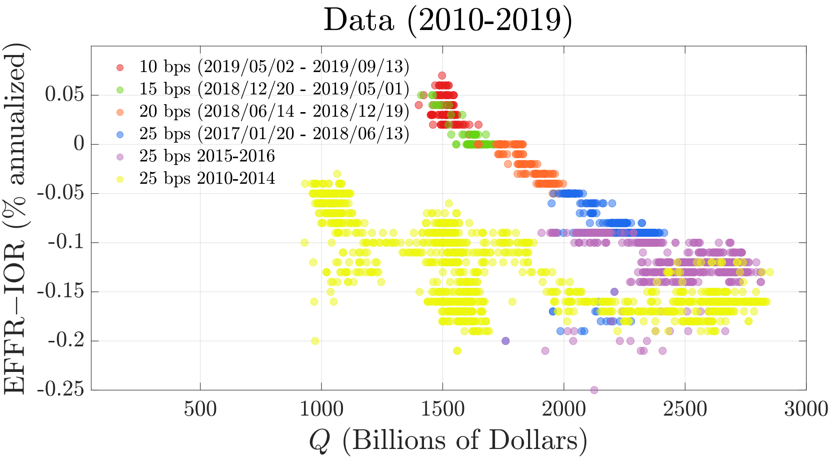
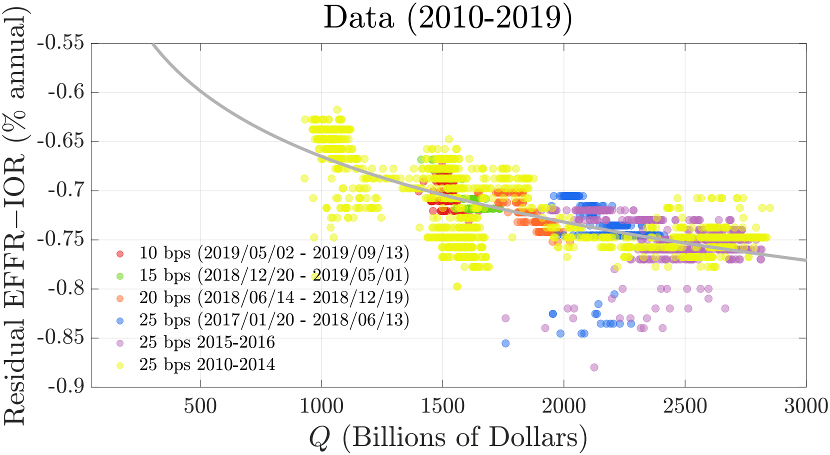


- 2010–2019, daily data split by IOR-ONRRP regime

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

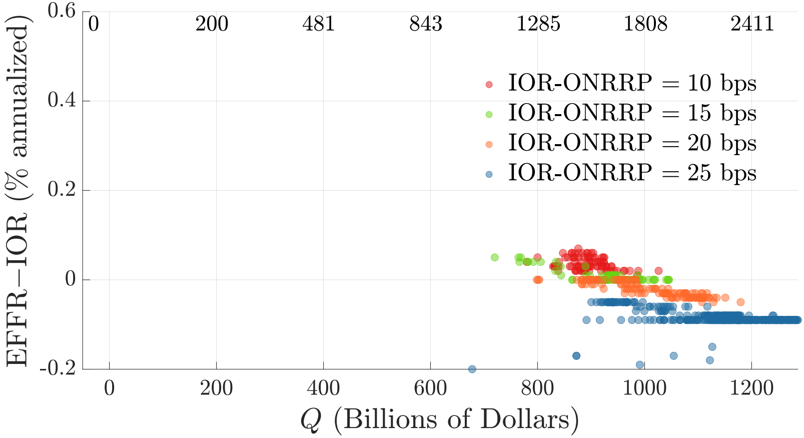


- 2010–2019, daily data split by IOR-ONRRP regime
- OLS fit of $y_t \equiv s_t - (\text{IOR-ONRRP dummies})$ on Q_t

Alternative demand estimations

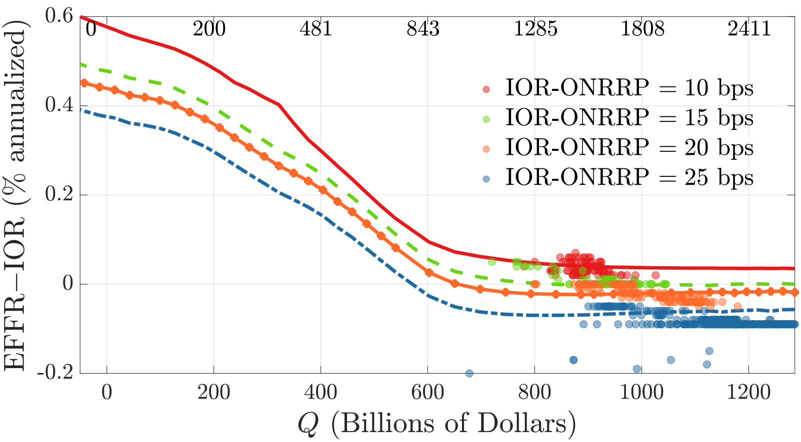
	(0)	(1)	(2)	(3)	(4)
$\ln(Q)$	-0.200	-0.219	-0.182	-0.156	-0.054
	(0.004)	(0.006)	(0.005)	(0.007)	(0.005)
$\ln(TD)$	0.363		0.320		
	(0.007)		(0.012)		
$\ln(DD)$		0.150		0.096	
		(0.005)		(0.005)	
$d_{25\text{bps}}$	no	no	yes	yes	yes
$d_{20\text{bps}}$	no	no	yes	yes	yes
$d_{15\text{bps}}$	no	no	yes	yes	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

Quantiative-theoretic estimation



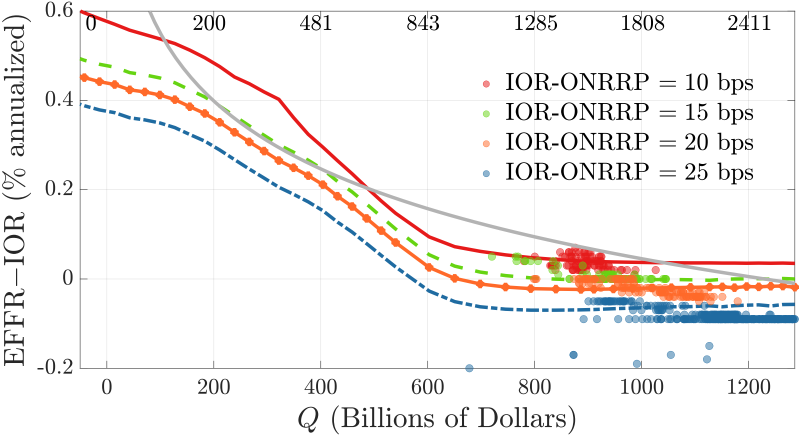
- Sample 2017/01/20–2019/09/13 split by IOR-ONRRP regime

Quantiative-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)

Quantiative-theoretic estimation



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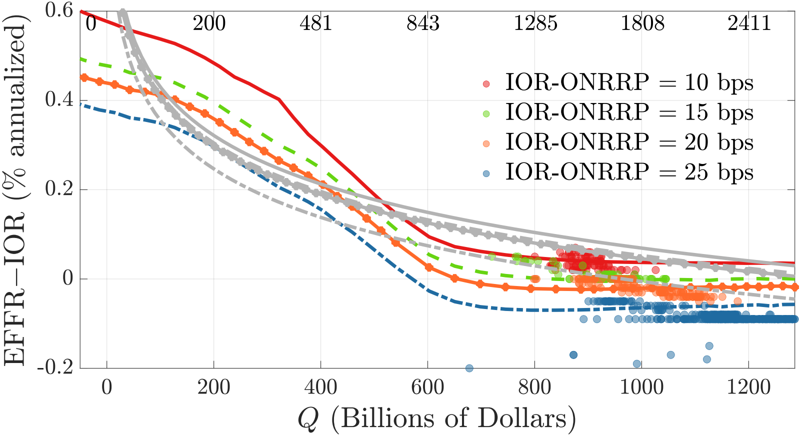
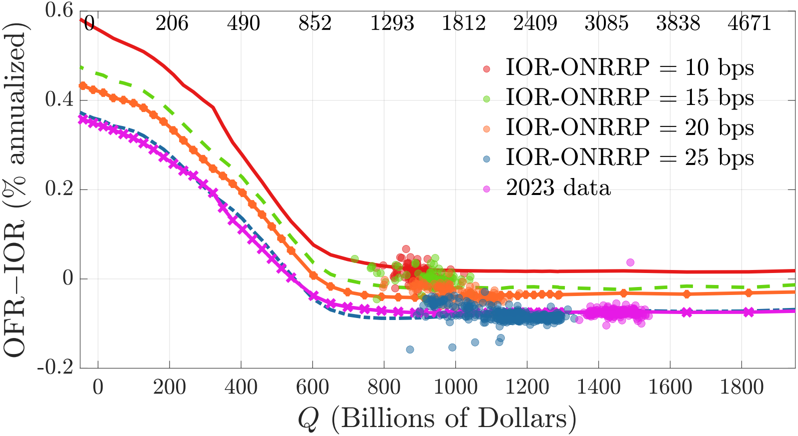


- Sample 2017/01/20–2019/09/13 split by IOR-ONRRP regime
- ADR implied by the theory (baseline calibration, but with administered rates to match the subsample)
- LS-VJ fit (2010-2019 sample, with demand deposits as control, and IOR-ONRRP-regime dummies)

Quantiative-theoretic estimation: Post COVID data



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 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)