The Liquidity State-Dependence of Monetary Policy

Oliver Ashtari-Tafti (LSE) Rodrigo Guimaraes (BoE) Gabor Pinter (BIS)
Jean-Charles Wijnandts (BoE)

New Evidence on the Monetary Transmission Mechanism

May 2024

Motivation

"The effectiveness of changes in central-bank targets for overnight rates in affecting spending decisions is wholly dependent upon the impact of such actions upon other financial-market prices such as longer-term interest rates, equity prices, and exchange rates. These are plausibly linked, through arbitrage relations to the short-term interest rates most directly affected by central-bank actions."

–Woodford (2003), *Interest & Prices*

- Growing consensus that frictions to arbitrage matter for asset prices and the macroeconomy

  Gromb & Vayanos (2002), He & Krishnamurthy (2013), Brunnermeier & Sannikov (2014)
- Frictions even in the most liquid market in the world: US Treasuries

  Duffie (2023) Jackson Hole
- Conventional monetary policy transmission relies on arbitrage, but even in liquid bond markets arbitrage is imperfect

This Paper

- **Research question:** how does bond market liquidity affect the transmission of conventional monetary policy shocks (MPS) to long-term rates?
- **Prior work:** puzzling (high) degree of Monetary Non-Neutrality
  Hanson & Stein (2015), Nakamura & Steinsson (2018)
- **Our work:** MPS transmission to long-term rates stronger & only happens when markets are more liquid $\rightarrow$ "Liquidity State-Dependence" (LSD)

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- **Our work:** MPS transmission to long-term rates stronger & only happens when markets are more liquid → "Liquidity State-Dependence" (LSD)
- Limits to arbitrage can explain the Liquidity State-Dependence
  ⇒ Nakamura & Steinsson (2018) meets Vayanos & Vila (2021)
- **Our contribution:** show arbitrageurs' wealth is the key state variable in explaining the Liquidity State-Dependence (not about macro)

The Liquidity State-Dependence (LSD)

1. Long-term nominal interest rates react more strongly to MPS when liquidity is high – Liquidity State-Dependence

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4. These state-dependent effects are persistent, lasting over a quarter
5. Persistent state-dependent response also for mortgage rates
   - It matters for the macroeconomy

- Robust to excluding recessions, QE dates, easing cycles and purging from the Fed Information Effect; also true in the UK

Understanding LSD: Theory

- We rationalize findings with limits-to-arbitrage and segmentation in bond markets as in Vayanos & Vila (2021)
  - Two agents: arbitrageurs trading all maturities and preferred-habitat investors (PH) with exogenous demand for individual maturities
  - Central bank in the background changes short-term interest rate MP shock
- **Arbitrageurs play two roles:**
  1. absorb demand shocks (including QE)
  2. only agents trading across the yield curve

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- Arbitrageurs wealth key to understand LSD of different MP tools
  - QE: largest during crisis and fully localized effects when no arbitrageurs
  - IR: no transmission when arbitrageurs are absent

$\Rightarrow$ opposite State-Dependent Effectiveness

Understanding LSD: Empirics

- **Hypothesis**: variation in arbitrageurs' wealth explains LSD
- Test the hypothesis using two independent data sources:

1. **Aggregate data**
   - Proxies for arbitrage capital (dealers' leverage, specific hedge fund strategies returns) most successful in explaining variation in liquidity
   - Capturing something beyond aggregate volatility, uncertainty or business cycle
   - Proxies for arbitrage capital can be directly used the 'state' in the SD
2. **Confidential transaction-level dataset**
   - Trades by UK-regulated entities in US Treasuries around FOMC meetings
   - We identify arbitrageurs from trading behavior in a way consistent with theory
   - More trading done by arbitrageurs in days where liquidity is high, particularly so for longer maturities

Roadmap

1. Literature, Data & Methodology
2. Main Results: Liquidity State-Dependence
3. The Role of Arbitrageurs in the Liquidity State-Dependence
   3.1 Evidence from Aggregate Data
   3.2 Evidence from Transaction-Level Data
4. Alternative Explanations
5. Conclusions

Literature

High-frequency Identification of Monetary Policy

Kuttner (2001), Cochrane & Piazzesi (2002), Bernanke & Kuttner (2005), Nakamura & Steinsson (2018), Jarocinski & Karadi (2020), Swanson (2021), Karnaukh & Vokata (2022), Bauer & Swanson (2023)

Monetary Policy and Risk Premia

Hanson & Stein (2015), Pflueger & Rinaldi (2020), Kekre & Lenel (2020), Hanson, Lucca & Wright (2021), Ai et al (2022), Bauer, Bernanke & Milstein (2023), Kashyap & Stein (2023), Nagel & Xu (2024)

The State-Dependence of Monetary Policy

Tenreyro & Thwaites (2016), Eichenbaum, Rebelo & Wong (2021)

Limits-to-Arbitrage in Bond Markets

Vayanos & Vila (2009, 2021), Ray (2019), King (2019), Ray, Droste & Gorodnichenko (2023), Kekre, Lenel & Mainardi (2024)

Data

Zero-coupon Yield Curves

- Nominal, TIPS and real (forward) curves from Gurkaynack, Sack and Swanson (2006)

High-frequency Monetary Policy Shocks

- Baseline with Nakamura & Steinsson (2018), updated by Acosta (2022)
- Robustness: Jarocinski & Karadi (2015), Bauer & Swanson (2023) and others

Bond-Market Liquidity Proxy

- Yield-curve 'noise' from Hu, Pan and Wang (2013)

Risk (Term) Premium Estimates

- Baseline with Abrahams et al (2015)
- Robustness with Kim & Wright (2005), D'Amico, Kim & Wei (2015)

Other Controls

- unemployment rate, PMI, business-conditions index from Aruoba et al (2009) VIX, MOVE, uncertainty measures Bauer & Chernov (2023) and Baekert et al (2020)

Aggregate Liquidity Proxy

- Our proxy for liquidity: yield-curve 'noise'
  - Measures cross-sectional dispersion ($\approx$ noise) of bond prices relative to a smooth yield curve
- Hu, Pan and Wang (2013) show that this measure is:
  - informative about overall market liquidity $\rightarrow$ more general than other bond market-specific measures
  - generally close to zero $\rightarrow$ smooth curve
  - closely correlated with arbitrageurs' capital (hedge fund returns, carry trade strategies), spiking during market stress (like LTCM and Lehman)
  - not driven by any individual maturity

$$\boxed{\uparrow \text{Liquidity} \Leftrightarrow \downarrow \text{Yield-Curve Noise}}$$

Empirical Specification

$$\Delta f_{j,t}^{(\tau)} = \alpha + \beta_j^{(\tau)} \cdot mps_t + \epsilon_{j,t}^{(\tau)} \qquad \text{(N\&S 2018)}$$

- $\Delta f_{j,t}^{(\tau)}$: daily change in maturity-τ forward rate
  - t: date of scheduled FOMC meeting
  - $j = \{Nominal(\text{n}), Real(\text{r}), Inflation(\text{i})\}$
  - $\tau = \{2, 3, 4, ..., 20\}$
- mps_t: high-frequency monetary policy shock

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- $\mathbb{1}_{\text{HighLiq}_{t-1}}$: dummy equal to 1 if noise < median noise before FOMC
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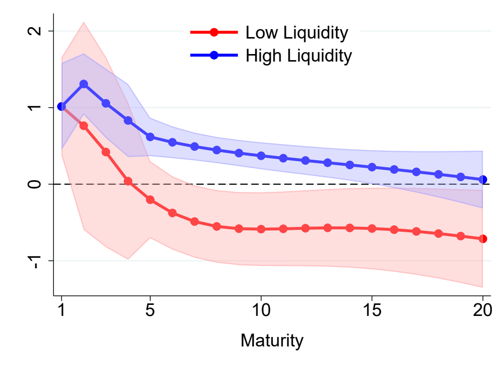
- Sample of Nakamura & Steinsson (2018)
  - 2000-2014, scheduled FOMC meetings, excl. GFC, N = 106
  - Robust to longer sample 2000-2019

Result 1: The Liquidity State-Dependence

$$\Delta f_{n,t}^{(\tau)} = \alpha + \beta_{n,hl}^{(\tau)} \cdot [mps_t \times \mathbb{1}_{\text{HighLiq}_{t-1}}] + \beta_{n,ll}^{(\tau)} \cdot [mps_t \times \mathbb{1}_{\text{LowLiq}_{t-1}}] + \epsilon_{n,t}^{(\tau)}$$

Nominal Forward Curve ▸ Spot ▸ Raw



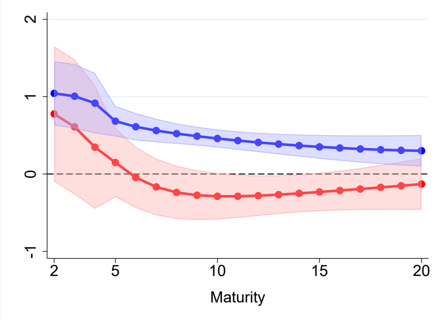
*Charts show point estimates and 95% confidence intervals for separate resgressions by maturity

Result 2: The Liquidity State-Dependence is Real

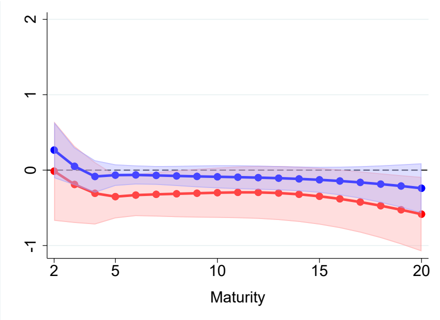
Fisher Identity: $f_{n,t}^{(\tau)} = f_{r,t}^{(\tau)} + f_{i,t}^{(\tau)}$

$$\Delta f_{j,t}^{(\tau)} = \alpha + \beta_{j,hl}^{(\tau)} \cdot [mps_t \times \mathbb{1}_{\text{HighLiq}_{t-1}}] + \beta_{j,ll}^{(\tau)} \cdot [mps_t \times \mathbb{1}_{\text{LowLiq}_{t-1}}] + \epsilon_{j,t}^{(\tau)}$$

Real Forward Curve
($j = r$)



Inflation Forward Curve
($j = i$)



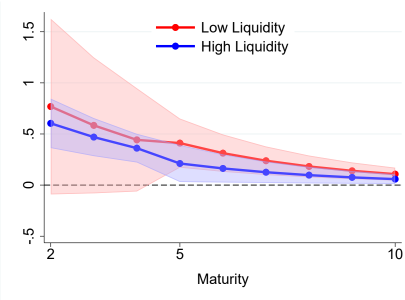
Result 3: Expectation Hypothesis vs Term Premium

Decomposition: $f_{r,t}^{(\tau)} = eh_{r,t}^{(\tau)} + rp_{r,t}^{(\tau)}$

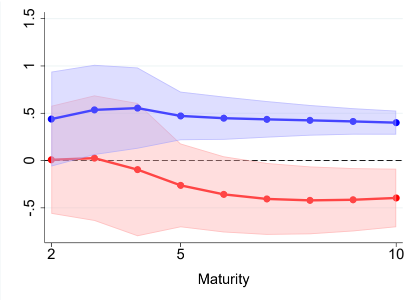
$$\Delta eh_{r,t}^{(\tau)} = \alpha + \beta_{r-eh,hl}^{(\tau)} \cdot [mps_t \times \mathbb{1}_{\text{HighLiq}_{t-1}}] + \beta_{r-eh,ll}^{(\tau)} \cdot [mps_t \times \mathbb{1}_{\text{LowLiq}_{t-1}}] + \epsilon_{r-eh,t}^{(\tau)}$$

$$\Delta rp_{r,t}^{(\tau)} = \alpha + \beta_{r-rp,hl}^{(\tau)} \cdot [mps_t \times \mathbb{1}_{\text{HighLiq}_{t-1}}] + \beta_{r-rp,ll}^{(\tau)} \cdot [mps_t \times \mathbb{1}_{\text{LowLiq}_{t-1}}] + \epsilon_{r-rp,t}^{(\tau)}$$

Real Expectations

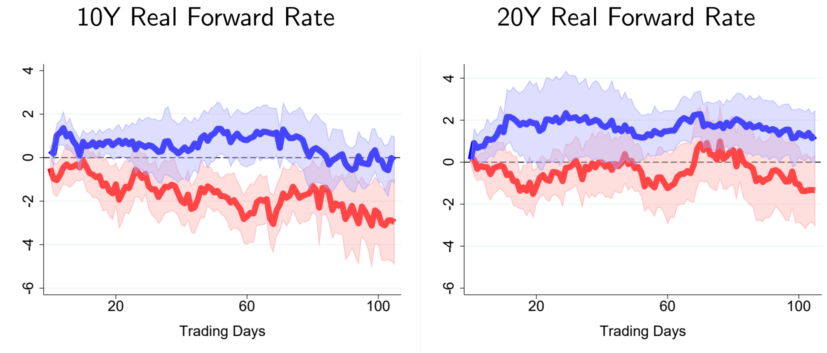


Real Risk Premium



Result 4: Persistence

$$f^{(\tau)}_{r,t+k} - f^{(\tau)}_{r,t-1} = \alpha_k + \beta^{(\tau)}_{r,k,hl} \cdot [mps_t \times \mathbb{1}_{\text{HighLiq}_{t-1}}] + \beta^{(\tau)}_{r,k,ll} \cdot [mps_t \times \mathbb{1}_{\text{LowLiq}_{t-1}}] + \epsilon^{(\tau)}_{r,t+k}$$



Understanding LSD:

The Role of Arbitrageurs

Inspecting the Mechanism - Roadmap

- Hu, Pan & Wang (2013) motivation: $\uparrow$ liquidity $\Leftrightarrow$ $\uparrow$ arbitrage capital
- Rationalize LSD with Vayanos & Vila (2021) with varying arbitrageurs capital
  - Poorly-capitalized arbitrageurs leads to weaker pass-through of MPS to long-term rates ▸ Model

$\uparrow$ Arbs' Capital ($\uparrow$ Liquidity) $\Leftrightarrow$ $\downarrow$ Yield-Curve Noise

- We validate this mechanism by separately testing two separate dimensions & independent data sources:
  1. **Aggregate data:** test if arbitrageurs capital can explain noise (& capture LSD)
  2. **Transaction-Level data:** test if arbitrageurs activity is higher in low-noise FOMC days

Inspecting the Mechanism - Aggregate Data

- **Question:** What explains our state variable, yield-curve noise?
  - Intermediary asset pricing theory predicts arbitrageurs capital, business cycle, volatility and asset prices should all co-move in equilibrium
    He & Krishnamurthy (2013), Brunnermeier & Sannikov (2014)
- Include proxies for arbitrageurs capital and competing alternatives:
  1. **Business cycle:** ADS index, real-time unemployment rate, PMI index
     Aruoba et al (2009), Berge & Jorda (2011)
  2. **Uncertainty/Risk:** VIX, MOVE, risk aversion and uncertainty indices, IR skewness, IR uncertainty
     Istrefi & Mouabbi (2018), Baekert et al (2020), Bauer & Chernov (2024)
  3. **Arbitrageurs capital:** intermediary capital factor, hedge fund returns (sub-indices for diff. strategies) from BarclayHedge
     He et al (2017)
- Univariate regression to assess economic significance of each variable
- Then horse race with all the variables together

What Explains Yield-Curve Noise?

$$\Delta \text{Noise}_t = \alpha + \beta \cdot X_t + \epsilon_t$$

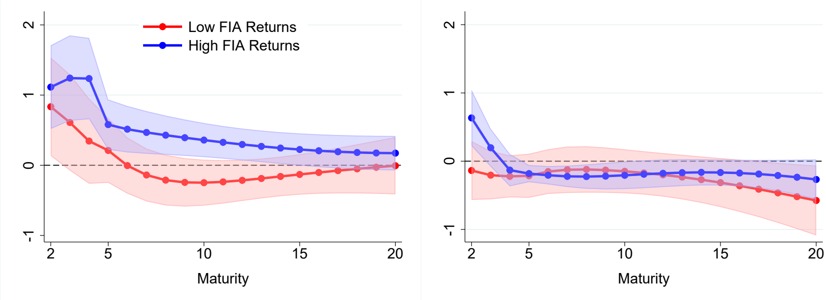
	Monthly Changes in Noise								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	AR(1)
ΔMOVE	0.02***							0.01***	
	(4.24)							(3.59)	
ΔUnemp.		0.14***						0.10***	
		(2.68)						(2.95)	
ΔUnc.			0.71**					-0.32	
			(2.44)					(-1.27)	
ΔLev.				1.43***				0.59*	
				(3.90)				(1.93)	
FIA Ret.					-0.41***		-0.18***	-0.17***	-0.32***
					(-7.95)		(-3.02)	(-2.63)	(-4.84)
ConvArb Ret.						-0.45***	-0.32***	-0.32***	-0.05
						(-5.35)	(-3.38)	(-2.82)	(-0.77)
Adj. R^2	15.94	2.53	16.10	16.35	34.52	40.89	43.47	50.77	18.76
N	205	240	240	240	240	240	240	205	239

- Arbitrageurs' proxies most successful at explaining monthly variation in noise, both in terms of univariate R^2 and surviving in full regression
- Evidence points to specialized investors and segmentation
  Duffie (2010), Siriwardane et al (2023)

State-Dependence with Fixed-Income Arb. Returns

$$\Delta f_{j,t}^{(\tau)} = \alpha + \beta_{j,hr}^{(\tau)} \cdot [mps_t \times \mathbb{1}_{HighFIAret_{t-1}}] + \beta_{j,lr}^{(\tau)} \cdot [mps_t \times \mathbb{1}_{LowFIAret_{t-1}}] + \epsilon_{j,t}^{(\tau)}$$

Real Forward Curve ($j = r$) | Inflation Forward Curve ($j = i$)



- Same state-dependence using FIA returns to define states
- Does not work with other proxies ▸ not Vol or Unc ▸ not MP easing cycles

Inspecting the Mechanism - Transaction-Level Data

- **Question:** is there more arbitrage capital (trading volume) around FOMC meeting when yield-curve noise is low?

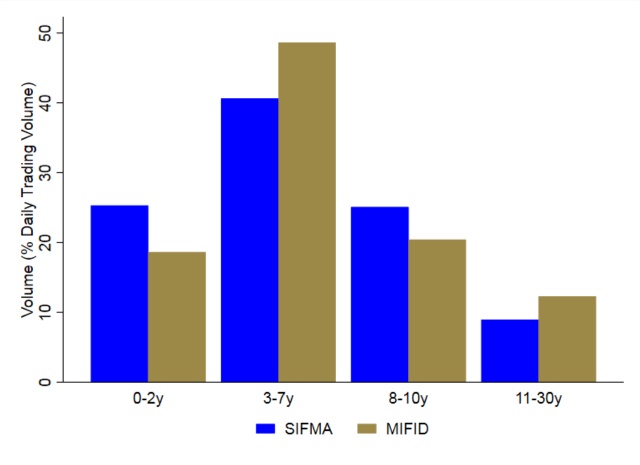
Inspecting the Mechanism - Transaction-Level Data

- **Question:** is there more arbitrage capital (trading volume) around FOMC meeting when yield-curve noise is low?
- We use the confidential MiFID II dataset kept by the Financial Conduct Authority (FCA)
- Trade-level, minute-by-minute dataset covering the universe of UK financial market participants
- Identify trading in US Treasuries

  Key advantages: coverage & frequency

  Limitations: shorter (and different) sample period (2018 - present)

Sample Representativeness



Identifying Arbitrageurs from Trading Characteristics

- Arbitrage is multi dimensional, attempt to capture along two dimensions:

1. Trading across the yield curve
   - We expect arbitrageurs to enforce arbitrage across different maturities
     $\Rightarrow$ standard deviation of maturities traded (weighted by notional)
2. Duration-neutral exposure
   - Captures the long-short nature of arbitrage
     $\Rightarrow$ net duration exposure of all trades

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- Each month, we rank traders along the two dimensions, we then create a composite score:

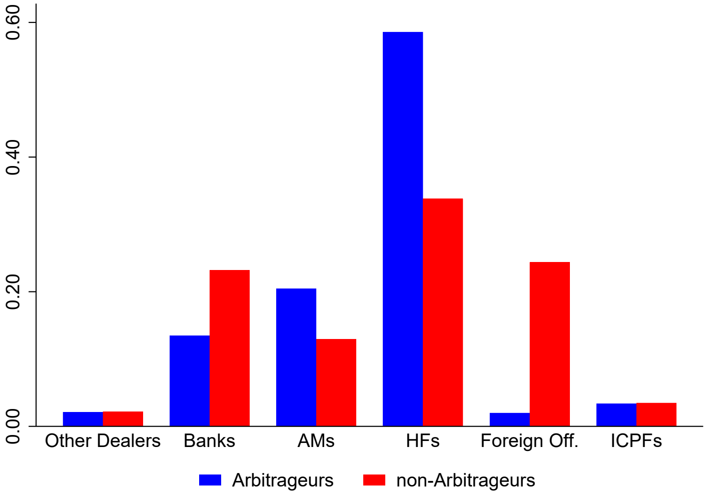
$$I_{i,t} = \rho^{\sigma}_{i,t} * \rho^{Dur}_{i,t}$$

- Then, average over the entire sample

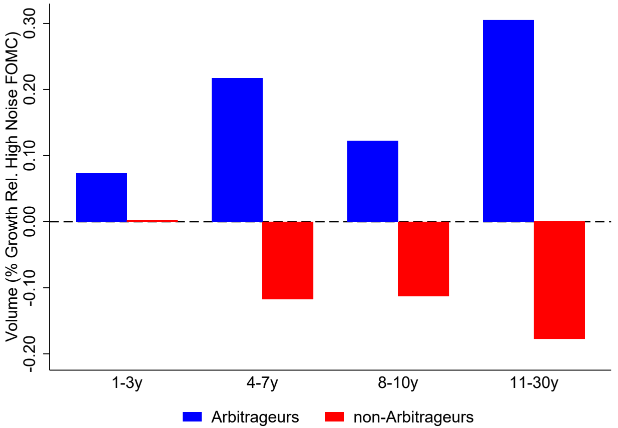
$$I_i = \frac{1}{N_{i,t}} \sum_{t=1}^{T} I_{i,t}$$

$\Rightarrow$ Arbitrageurs are IDs in the top-tercile of the index

Who are the Arbitrageurs?



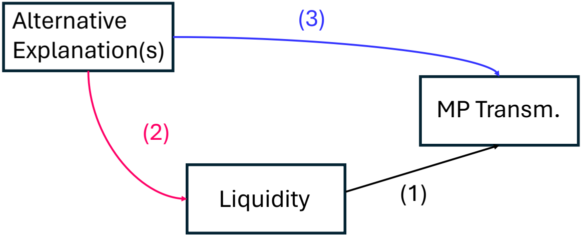
Arbitrageurs Trade More When Noise is Low



- Arbs > 0, increase trading (almost) monotonically across maturities
  - Between 15%-25% more trading in the High Liquidity days relative to Low Liquidity days
- Non-arbs < 0: they trade less

Alternative Explanations

Alternative Explanations: Business Cycles, QE & Volatility



- We have shown (2) unlikely
- What can we say about (3)?
  - Tenreyro & Thwaites (2016) show MP less powerful in recessions/easing cycles

Recessions, QE Dates and Easing Cycles

	Nominal				Real				Inflation			
	2Y	5Y	10Y	15Y	2Y	5Y	10Y	15Y	2Y	5Y	10Y	15Y
	A. LSD excluding NBER recessions											
High Liquidity	1.05***	0.54***	0.27*	0.15	1.18***	0.68***	0.37***	0.26**	0.18	-0.14	-0.10	-0.12
	(3.87)	(4.21)	(2.46)	(1.17)	(4.75)	(5.84)	(4.27)	(2.91)	(1.00)	(-1.81)	(-1.43)	(-1.47)
Low Liquidity	1.39**	0.09	-0.61*	-0.68*	2.16*	0.63	-0.14	-0.20	-0.54	-0.54*	-0.46*	-0.47*
	(2.73)	(0.24)	(-2.06)	(-2.29)	(2.42)	(1.72)	(-0.69)	(-1.10)	(-1.71)	(-2.59)	(-2.43)	(-2.10)
	B. LSD excluding QE dates											
High Liquidity	0.99***	0.48***	0.27*	0.13	1.11***	0.64***	0.36***	0.26**	0.16	-0.16*	-0.09	-0.13
	(3.81)	(4.09)	(2.47)	(0.99)	(4.59)	(5.98)	(4.09)	(2.79)	(0.88)	(-2.05)	(-1.27)	(-1.53)
Low Liquidity	0.97*	-0.11	-0.65**	-0.69**	1.73**	0.32	-0.26	-0.24	-0.39	-0.43**	-0.39*	-0.44**
	(2.49)	(-0.43)	(-3.05)	(-3.02)	(2.64)	(1.30)	(-1.74)	(-1.88)	(-1.20)	(-2.80)	(-2.50)	(-2.66)
	C. MPS impact by observed target rate decision (no change, hike, easing)											
nochange	1.57***	0.64**	0.05	-0.07	1.55***	0.93***	0.25	0.12	0.10	-0.29*	-0.20	-0.20
	(8.72)	(3.17)	(0.30)	(-0.40)	(4.48)	(4.85)	(1.65)	(0.96)	(0.49)	(-2.38)	(-1.89)	(-1.48)
hike	1.32***	0.39	-0.20	-0.18	1.58***	0.56*	0.26	0.16	-0.18	-0.17	-0.46*	-0.34
	(3.57)	(1.19)	(-0.75)	(-0.69)	(3.67)	(2.12)	(1.32)	(0.62)	(-0.49)	(-0.83)	(-2.39)	(-1.94)
ease	0.35	0.04	0.02	-0.07	0.34	0.23	0.10	0.10	-0.09	-0.19	-0.08	-0.17
	(0.98)	(0.20)	(0.08)	(-0.28)	(0.75)	(1.36)	(0.61)	(0.60)	(-0.23)	(-1.87)	(-0.71)	(-1.49)

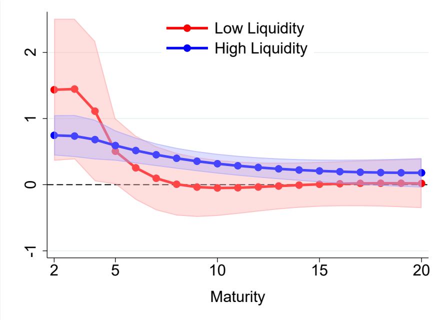
- LSD not about recessions or QE shocks (also present pre-2007)
- Stark difference during easing cycles (confirms Tenreyro & Thwaites (2016) but in yield curve space): could this explain LSD?

Liquidity-SD without Easing Cycle

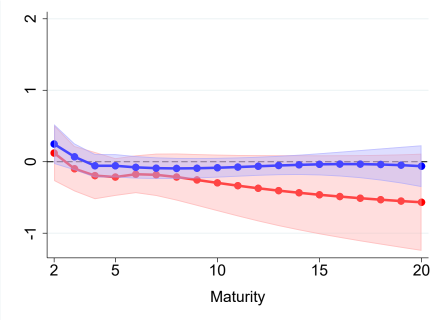
$\Rightarrow$we now exclude all FOMC meetings when target rate was cut

$$\Delta f_{j,t}^{(\tau)} = \alpha + \beta_{j,hl}^{(\tau)} \cdot [mps_t \times \mathbb{1}_{\text{HighLiq}_{t-1}}] + \beta_{j,ll}^{(\tau)} \cdot [mps_t \times \mathbb{1}_{\text{LowLiq}_{t-1}}] + \epsilon_{j,t}^{(\tau)}$$

Real Forward Curve
($j = r$)



Inflation Forward Curve
($j = i$)



Conclusions

- We document a strong Liquidity State-Dependence in transmission of MP shocks to yield curve: 'non-neutrality puzzle' only in liquid markets

- The Liquidity State-Dependence is entirely about the long-term real rates and it is persistent: it matters for macroeconomic policy

- We show our results linked to presence of arbitrageurs, providing two distinct pieces of evidence: using aggregate data and using transaction-level data

- Policy complementarity: market functioning/liquidity in bond markets important for both financial stability and monetary policy

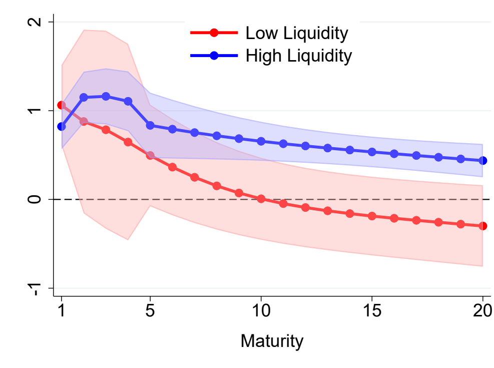
Backup Slides

State-Dependence with Spot Rates

$y_{n,t}^{(\tau)} = \frac{1}{\tau}\sum_{j=1}^{\tau} f_{n,t}^{(j)}$

$$\Delta y_{n,t}^{(\tau)} = \alpha + \beta_{n,hl}^{(\tau)} \cdot [mps_t \times \mathbb{1}_{\text{HighLiq}_{t-1}}] + \beta_{n,ll}^{(\tau)} \cdot [mps_t \times \mathbb{1}_{\text{LowLiq}_{t-1}}] + \epsilon_{n,t}^{(\tau)}$$

Nominal Spot Curve



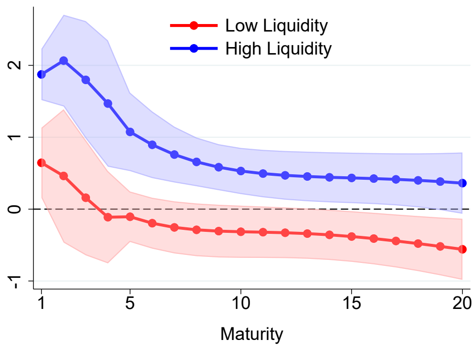
back

Liquidity State-Dependence with *Raw* MPS & Noise

LSD even stronger without normalizing & detrending

$$\Delta f_{n,t}^{(\tau)} = \alpha + \beta_{n,hl}^{(\tau)} \cdot [mps_t \times \mathbb{1}_{\text{HighLiq}_{t-1}}] + \beta_{n,ll}^{(\tau)} \cdot [mps_t \times \mathbb{1}_{\text{LowLiq}_{t-1}}] + \epsilon_{n,t}^{(\tau)}$$

Nominal Forward Curve

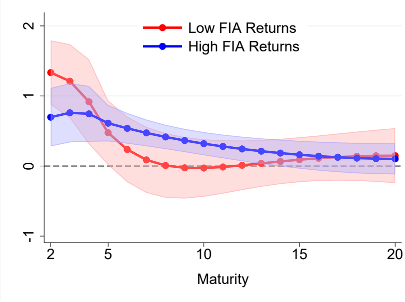


back

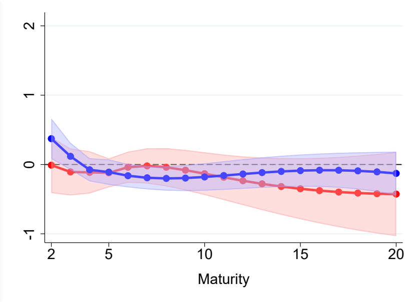
Fixed Income Arbitrage Return-SD without Easing Cycle

$$\Delta f^{(\tau)}_{j,t} = \alpha + \beta^{(\tau)}_{j,hr} \cdot [mps_t \times \mathbb{1}_{HighFIAret_{t-1}}] + \beta^{(\tau)}_{j,lr} \cdot [mps_t \times \mathbb{1}_{LowFIAret_{t-1}}] + \epsilon^{(\tau)}_{j,t}$$

Real Forward Curve
$(j = r)$



Inflation Forward Curve
$(j = i)$



- Same state-dependence using FIA returns to define states when we exclude all FOMC meetings when target rate was cut

back

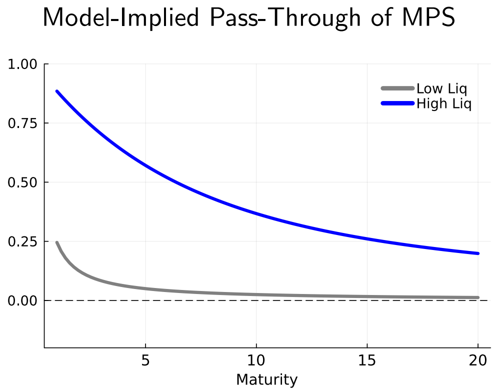
State-dependence with Volatility or Uncertainty?

	Nominal				Real				Inflation			
	2Y	5Y	10Y	15Y	2Y	5Y	10Y	15Y	2Y	5Y	10Y	15Y
	A. sorting on MOVE											
low MOVE	1.09***	0.27	-0.20	-0.26	1.07***	0.66**	-0.05	-0.16	0.03	-0.40**	-0.15	-0.11
	(4.11)	(1.06)	(-1.01)	(-1.35)	(3.91)	(3.00)	(-0.26)	(-0.78)	(0.21)	(-2.74)	(-1.22)	(-0.75)
high MOVE	1.06**	0.30	-0.06	-0.14	1.07**	0.50*	0.14	0.12	-0.10	-0.21*	-0.21*	-0.26*
	(3.32)	(1.29)	(-0.34)	(-0.70)	(3.16)	(2.46)	(0.99)	(0.92)	(-0.51)	(-2.33)	(-2.28)	(-2.35)
	B. sorting VIX											
low VIX	1.10***	0.45**	0.03	-0.02	1.01***	0.69***	0.14	0.04	0.09	-0.24**	-0.11	-0.06
	(7.36)	(3.00)	(0.23)	(-0.13)	(5.07)	(5.00)	(1.19)	(0.37)	(0.74)	(-3.06)	(-1.79)	(-0.80)
high VIX	0.76*	0.06	-0.23	-0.32	1.20*	0.31	0.04	0.03	-0.32	-0.25*	-0.27*	-0.35*
	(2.42)	(0.28)	(-1.02)	(-1.43)	(2.33)	(1.59)	(0.28)	(0.22)	(-1.11)	(-2.15)	(-2.16)	(-2.60)
	C. sorting Interest Rate Uncertainty (Istrefi & Mouabbi (2018))											
low IR Unc.	1.14***	0.53**	-0.04	-0.08	1.35***	0.78***	0.16	-0.01	-0.20	-0.24*	-0.20	-0.08
	(5.48)	(2.75)	(-0.31)	(-0.70)	(5.65)	(4.44)	(1.24)	(-0.05)	(-1.15)	(-2.03)	(-1.77)	(-0.75)
high IR Unc.	0.78**	0.13	-0.11	-0.20	0.89*	0.34	0.08	0.08	0.12	-0.21*	-0.19	-0.27*
	(2.68)	(0.67)	(-0.53)	(-0.99)	(2.58)	(1.94)	(0.59)	(0.63)	(0.46)	(-2.38)	(-1.84)	(-2.40)
	D. sorting Uncertainty (Bekaert, Engstrom & Xu (2022))											
low Uncert.	0.92**	0.28	-0.12	-0.17	1.24***	0.45*	0.14	0.08	0.22	-0.17*	-0.26**	-0.25**
	(3.17)	(1.39)	(-0.80)	(-1.32)	(5.33)	(2.27)	(1.27)	(0.81)	(1.20)	(-2.47)	(-2.93)	(-2.84)
high Uncert.	1.13**	0.23	-0.16	-0.27	1.70**	0.63*	0.04	0.00	-0.38	-0.40*	-0.20	-0.27
	(2.79)	(0.79)	(-0.55)	(-0.92)	(2.67)	(2.31)	(0.20)	(0.00)	(-1.26)	(-2.59)	(-1.35)	(-1.56)

back

Model

Vayanos & Vila (2021) with varying mass of arbitrageurs

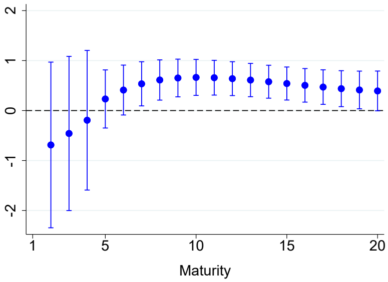


back

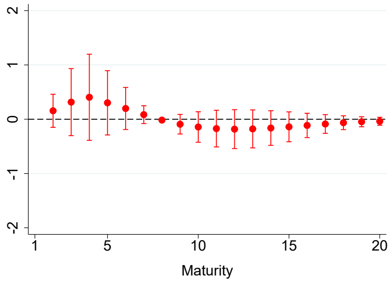
Is it Business Cycle State-Dependence?

$$\Delta f_{r,t}^{(\tau)} = \alpha + \beta \cdot mps_t + \gamma_{H-L} \cdot [mps_t \times \text{HighLiq}_{t-1}] + \delta \cdot [mps_t \cdot \text{GoodMacro}_{t-1}] + \nu_{r,t}^{(\tau)}$$

High Liquidity State, γ_{H-L}



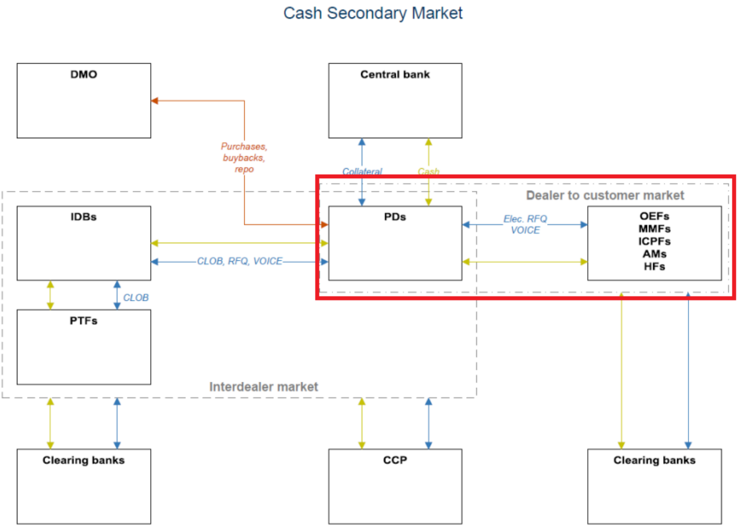
Good Macro State*, δ



- Liquidity-SD in long-term rates after accounting for macro-SD
- Macro-SD matters short-term rates but not significant

* GoodMacro refers to FOMC meetings where latest PMI was above its median

Summary Statistics: Dealer-to-Client Segment



Summary Statistics: Dealer-to-Client Segment

	Volume	No. Transactions	Trade Size	No. LEI
	Panel A: Full Sample			
	9,887	586	16.9	3,020
	Panel B: By Maturity			
1-3y	2,676 (26.3%)	132 (22.0%)	20.2	2,146
3-7y	3,433 (33.8%)	153 (25.5%)	22.4	2,067
7-10y	2,831 (27.9%)	189 (31.5 %)	15.0	2,199
11-30y	1,218 (12.0%)	126 (21.0%)	9.7	1,806
	Panel C: By Sector			
Banks	3,829 (37.2%)	293 (48.5%)	13.0	524
AMs	1,329 (12.9%)	168 (27.8%)	7.9	1,365
HFs	3,160 (30.7%)	83 (13.7%)	38.1	596
Foreign Off.	1,654 (16.1%)	38 (6.3%)	43.5	126
ICPFs	308 (3.0%)	22 (3.6%)	14.1	409

]

Identifying Arbitrage Capital

		Volume	No. Transactions	Trade Size	No. LEI
		Panel A: Any Day			
RV		2,372	103	23.0	699
non RV		7,610	488	15.6	2,321
		Panel B: FOMC			
RV	no FOMC	2,342	101	23.1	699
RV	Pre-FOMC (t)	2,716	127	21.4	459
RV	Post-FOMC (t+1)	3,155	143	22.0	479
non RV	no FOMC	7,498	482	15.6	2,285
non RV	Pre-FOMC (t)	8,830	556	15.9	957
non RV	Post-FOMC (t+1)	10,545	662	15.9	922
		Panel C: High vs Low Liquidity FOMC			
RV	H-Noise Pre-FOMC	2,305	111	20.8	310
RV	H-Noise Post-FOMC	2,873	137	21.0	329
RV	L-Noise Pre-FOMC	3,034	139	21.8	375
RV	L-Noise Post-FOMC	3,374	148	22.8	394
non RV	H-Noise Pre-FOMC	8,255	475	17.4	615
non RV	H-Noise Post-FOMC	10,931	640	17.1	637
non RV	L-Noise Pre-FOMC	9,274	618	15.0	802
non RV	L-Noise Post-FOMC	10,246	680	15.1	761