Liquidity Supply and Demand in the Corporate Bond Market

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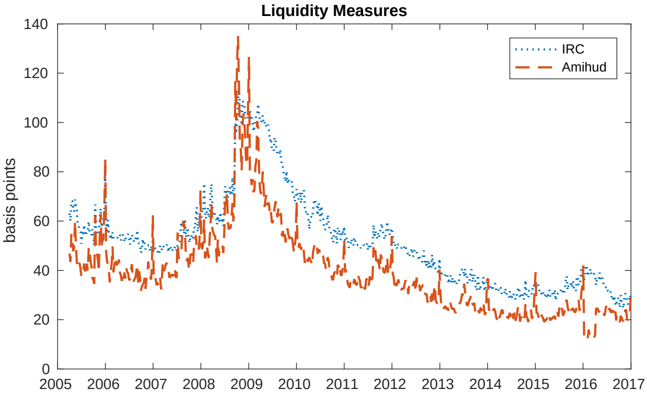
The views expressed here are those of the authors and need not represent the views of the Federal Reserve Board or its staff.

Motivation

- Estimated transaction costs for corporate bonds have declined since the financial crisis.



Improved Liquidity?

- Popular press says the opposite:
  - Big Bond Investors Say Liquidity Has Declined in Past Year (WSJ, May 31, 2016)
  - Liquidity Specter Haunts Corporate-Bond Markets (WSJ, Jan 11, 2015)
    - "Corporate-Debt Issuance Is at Records, but Trading Problems Remain a Worry for Investors"
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  - Bond liquidity risks top fund managers' agenda (FT, May 15, 2015)
    - Industry body to contact investors, warning of the risks
- Backgrounds
  1. Banking regulations: Supplemental leverage ratio, CCAR, the Volker rule
  2. Changing investor base: Rise of Corporate bond ETFs, mutual funds
  3. Increasing new issuances

Challenge

- Changing transaction costs can be due to:
  1. More supply of liquidity
  2. Less demand of liquidity
- By looking at the transaction costs, we cannot tell 1 or 2.
- We have to look at *price* and *quantity* to tell the different drivers of liquidity.
- Other questions which cannot be answered without a unifying framework of liquidity supply and demand.
  1. Why is liquidity priced in asset prices?
  2. Do liquidity supply and demand shocks carry different price of risk?

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What We Do

- Build a simple model of segmented markets following Gromb and Vayanos (2002)
- Define the price and quantity of liquidity
  - Price: Noise in the corporate bond yield curve
  - Quantity: Aggregate dealers' gross positions on corporate bonds
- Structural VAR with sign restrictions
  - Run a VAR with price and quantity
  - Supply shocks: move price and quantity in the opposite direction
  - Demand shocks: move price and quantity in the same direction
  - Bayesian estimates in which we jointly estimate reduced-form and structural VARs
- Use estimated VAR to study the impact of banking regulations and the source of liquidity premiums.

Literature

- Liquidity measures for corporate bonds
  Chen, Lesmond and Wei (2007), Edwards, Harris and Piwowar (2007), Bao, Pan and Wang (2011), Feldhutter (2012), Dick-Nielsen, Feldhutter, and Lando (2012)
- Effect of recent banking regulations on dealer balance sheet
  Adrian, Boyarchenko and Shachar (2017), Anand, Jotikasthira and Venkataraman (2017), Bessembinder, Jacobsen, Maxwell and Venkataraman (2017), Bao, O'Hara and Zhou (2017), Choi and Huh (2017), Friewald and Nagler (2017), Goldstein and Hotchkiss (2017), Trebbi and Xiao (2015)
- Supply and demand analysis
  Macroeconomics: Arias, Rubio-Ramirez and Waggoner (2016), Baumeister and Hamilton (2015), Faust (1998), Kilian and Murphy (2012), Uhlig (2005, 2015)
  Finance: Cohen, Diether and Malloy (2007), Chen, Joslin and Ni (2017)
- Theory of segmented markets
  Greenwood, Hanson and Liao (2016), Gromb and Vayanos (2002, 2017), Shleifer and Vishny (1997), Vayanos and Villa (2009)

Theory of Segmented Markets

- Time periods, 1, 2, and 3
- Two investors, A and B
- Two securities, A and B: Claim on an uncertain cash flow ν in time 3
  - $E[\nu] = \mu$
  - $Var[\nu] = \sigma$
- i-investors can trade only i-bond and cash: $i \in \{A, B\}$
- Each security has net supply g
- Gross-interest rate is normalized to one.
- i-investor has a preference

$$E[w_i] - \frac{1}{2\gamma} Var[w_i]$$

- Hedging motive: endowment at time 3 given by $e_A = -e_B$ and $Cov(\nu, e_A) = u > 0$.

Theory of Segmented Markets

- Dealers can trade both securities
- Cash flow ν is revealed in time 2.
- With probability λ, forced to liquidate positions at $p_{i,2} = \nu + \varepsilon_i$
- Preference: $E[w_D] - \frac{1}{2\gamma_D} Var[w_D]$
- Time 1 risk premia

$$\varphi_i = \mu - p_{i,1}$$

- Define

$$g^* = \left(1 + \frac{2\gamma\sigma}{\gamma_D\sigma + \gamma\lambda\sigma_\varepsilon}\right)\frac{u}{\sigma} > 0$$

- Assume $|g| < g^* \Rightarrow$In equilibrium, the dealer has positions $x_A > 0$ and $x_B < 0$

Equilibrium

- Dealers' payoffs have a variance-covariance matrix by

$$\Omega = \begin{bmatrix} \sigma + \lambda\sigma_\varepsilon & \sigma \\ \sigma & \sigma + \lambda\sigma_\varepsilon \end{bmatrix}$$

- Dealers' positions are given by $x = \gamma_D \Omega^{-1} \varphi$.
- Investors' positions are given by

$$y = \frac{1}{\sigma}\left(\gamma\varphi - u \begin{bmatrix} 1 \\ -1 \end{bmatrix}\right).$$

- Market clearing: $x + y = g$

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- Market clearing: $x + y = g$
- Price dispersion is

$$\frac{|p_{B,1} - p_{A,1}|}{2} = \frac{1}{\gamma_D \frac{1}{\lambda}\frac{\sigma}{\sigma_\varepsilon} + \gamma} u$$

- Dealer *gross* position is

$$\frac{|x_A| + |x_B|}{2} = \frac{1}{\sigma + \frac{\gamma}{\gamma_D}\lambda\sigma_\varepsilon} u$$

Proposition

1. An increase in dealer risk tolerance γ_D leads to lower price dispersion and higher dealer gross positions.

$$
\begin{aligned}
\frac{d\left[\left|p_{B,1} - p_{A,1}\right|\right]}{d\gamma_D} &< 0, \\
\frac{d\left[\left|x_A\right| + \left|x_B\right|\right]}{d\gamma_D} &> 0.
\end{aligned}
$$

$\Rightarrow$A Supply Shock.

Proposition

1. An increase in dealer risk tolerance γ_D leads to lower price dispersion and higher dealer gross positions.

$$\frac{d\left[|p_{B,1} - p_{A,1}|\right]}{d\gamma_D} < 0,$$
$$\frac{d\left[|x_A| + |x_B|\right]}{d\gamma_D} > 0.$$

$\Rightarrow$A Supply Shock.

2. An increase in investor risk tolerance γ_i (or a decrease in investor trading needs u) leads to lower price dispersion and lower gross positions.

$$\frac{d\left[|p_{B,1} - p_{A,1}|\right]}{d\gamma_i} < 0,$$
$$\frac{d\left[|x_A| + |x_B|\right]}{d\gamma_i} < 0.$$

$\Rightarrow$A Demand Shock.

Liquidity Quantity

- Primary dealers' aggregate gross positions on corporate bonds.

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- Regulatory TRACE from 2005 to 2016: Trade with a dealer identity
  - Cumulate trades for each CUSIP for each dealer: LIFO method.
  - Weekly inventory data
    - Remove trades with volume greater than 1/3 of amount outstanding
    - Remove trades that are not closed within four weeks
  - Aggregate across dealers d
  - Aggregate across CUSIP k and across issuer j

$$q_t = \log \sum_j \sum_k \sum_d |Q_{d,j,k,t}|$$

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$$q_t = \log \sum_j \sum_k \sum_d |Q_{d,j,k,t}|$$

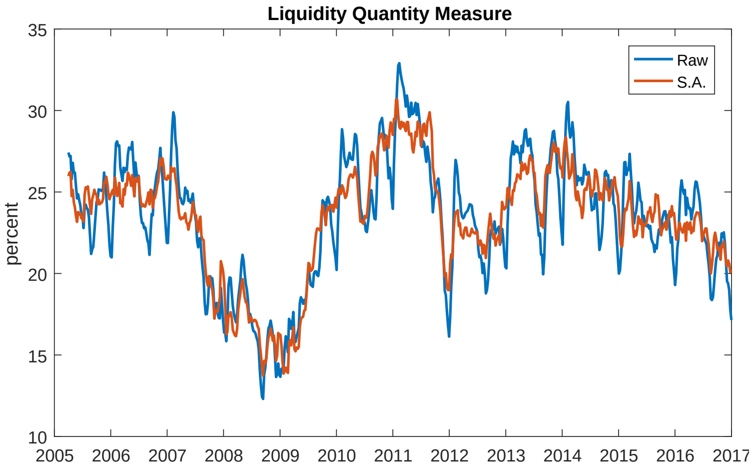
- Senior, unsecured US dollar-denominated bonds with no optionalities other than make-whole calls.
- 18,986 bonds issued by 4,466 issuers from April 2005 to December 2016

Liquidity Quantity

The LIFO method.

ID	Week	Volume	Amount Outstanding 1	2	3	4	5	End-of-Week Inventory
1	1	1000	1000					1000
2	2	200	1000	200				1200
3	3	-300	900	0	0			900
4	4	-500	400	0	0	0		400
5	5	100	**0**	0	0	0	100	100

Liquidity Quantity



(Correlation with FR-2004 since April 2013 = 0.58)

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- Merrill Lynch U.S. Corporate Master Database.
- Same filters as quantity, plus additional requirement that an issuer has more than 7 bonds (NS) or 15 bonds (NSS) outstanding.

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- Merrill Lynch U.S. Corporate Master Database.
- Same filters as quantity, plus additional requirement that an issuer has more than 7 bonds (NS) or 15 bonds (NSS) outstanding.
- Fit Nelson-Siegel-Svennson curve given by

$$f(n) = \beta_0 + \beta_1 \exp(-n/\tau_1) + \beta_2 (n/\tau_1) \exp(-n/\tau_1) + \beta_3 (n/\tau_2) \exp(-n/\tau_2)$$

- Liquidity price measure is given by

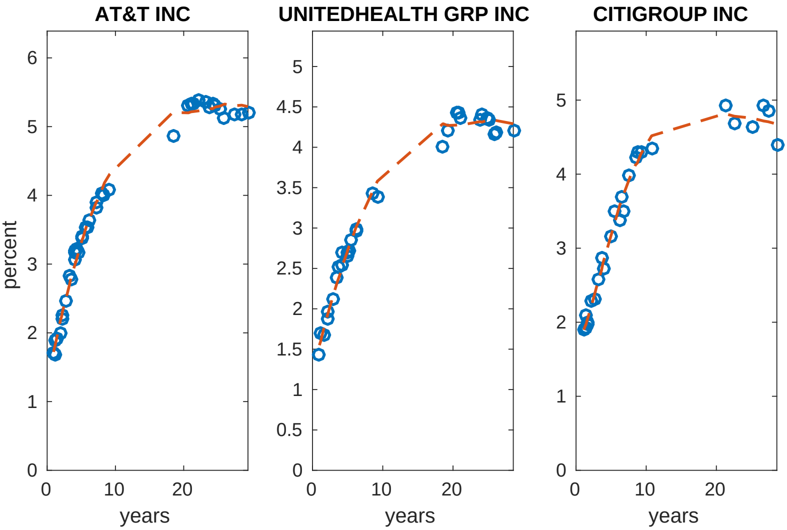
$$p_t = \frac{1}{J} \sum_j \sqrt{\frac{1}{K_j} \sum_k \epsilon_{k,j,t}^2}.$$

where $\epsilon_{k,j,t}$ is the difference in yield between bond k and the curve.

- 3,040 bonds issued by 169 issuers.

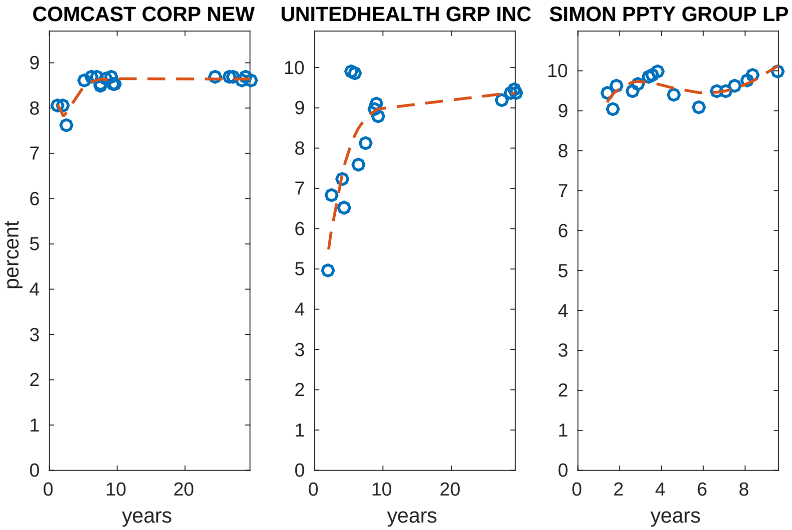
Noise

Figure: Yield to Maturity on Dec 23,2016

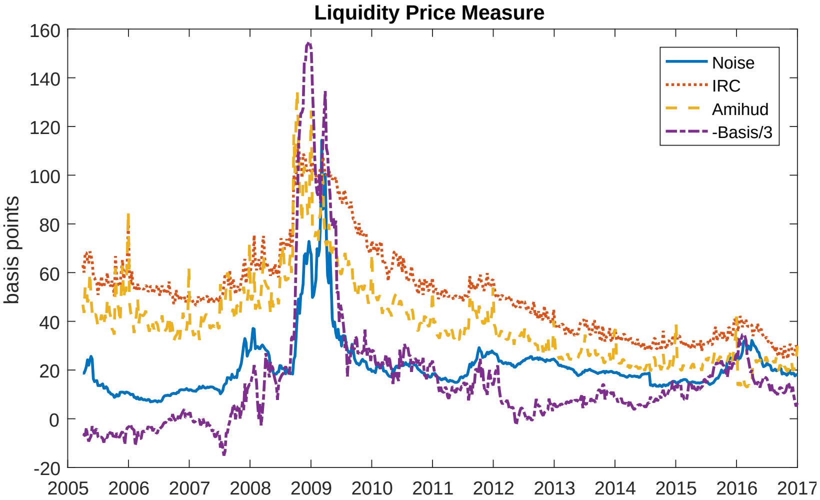


Noise

Figure: Yield to Maturity on Oct 24,2008



Liquidity Price



Selection Bias

Comparison between Bonds in the Price Sample and Others

		NObs	IRC	Amihud	Vol
Panel A: Correlation Between Matched and Unmatched Bonds					
All			0.96	0.94	0.89
IG			0.95	0.94	0.85
HY			0.72	0.78	0.73
Panel B: Average values and number of observations					
All	Matched	376,171	0.55	0.44	10320
	Unmatched	1,495,208	1.89	0.62	7420
IG	Matched	351,562	0.52	0.42	10482
	Unmatched	925,402	0.65	0.57	7867
HY	Matched	24,609	0.82	0.64	8014
	Unmatched	569,806	3.79	0.68	6695

TRACE versus Merrill Lynch Data

Average yield to maturity

	Merrill Lynch				TRACE			
	-4yr	4-7yr	7-12yr	12yr-	-4yr	4-7yr	7-12yr	12yr-
AAA	3.39	4.03	4.40	4.97	3.31	3.99	4.35	4.96
AA	2.99	3.86	4.55	5.12	2.92	3.81	4.51	5.10
A	2.88	3.76	4.51	5.31	2.82	3.72	4.48	5.29
BBB	3.34	4.28	4.92	5.87	3.28	4.24	4.89	5.85
HY	11.18	9.57	8.12	9.36	11.01	9.44	8.06	9.25

Note: Average yield to maturity of bonds that show up both in TRACE and Merrill Lynch. 229,228 bond-month observations.

TRACE versus Merrill Lynch Data

End of year only

	Merrill Lynch				TRACE			
	-4yr	4-7yr	7-12yr	12yr-	-4yr	4-7yr	7-12yr	12yr-
AAA	3.24	4.24	4.54	4.83	3.08	4.07	4.44	4.78
AA	3.03	3.82	4.55	5.08	2.91	3.72	4.46	5.04
A	2.85	3.83	4.70	5.39	2.74	3.71	4.61	5.33
BBB	4.00	4.50	5.24	6.14	3.86	4.37	5.16	6.11
HY	16.34	11.81	8.86	12.95	16.05	11.70	8.78	12.46

Note: Average yield to maturity of bonds that show up both in TRACE and Merrill Lynch. 7,468 bond-month observations.

Summary Statistics

	Mean	Std	AR1	AR12
q	16.95	0.18	0.98	0.67
p	21.45	12.24	0.97	0.68

	p	Amihud	IRC	Basis
q	-0.57	-0.59	-0.51	0.54
p		0.57	0.61	-0.86
Amihud			0.93	-0.62
IRC				-0.66

Structural VAR

- The reduced form VAR is

$$Y_t = b + B_1 Y_{t-1} + \ldots + B_L Y_{t-L} + \xi_t$$

where $Y_t = \begin{pmatrix} p_t & q_t \end{pmatrix}'$ and $E[\xi\xi'] = \Sigma$.
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- $L = 6$ based on AIC
- Structural shocks v is obtained from the rotation $v = A^{-1}\xi$
- Identify A with a **sign restriction**:

$$\begin{pmatrix} \xi_t^p \\ \xi_t^q \end{pmatrix} = \underbrace{\begin{pmatrix} - & + \\ + & + \end{pmatrix}}_{A} \begin{pmatrix} v_t^s \\ v_t^d \end{pmatrix}$$

- Bayesian estimation

Sign Restriction

- Use weak Normal-Wishart prior for B and Σ.

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2. Given B_i and Σ_i, do the following:
   - 2.1 Draw entries for 2-by-2 matrix W from a standard normal distribution
   - 2.2 Apply the QR decomposition to obtain orthogonal matrix Z_W
   - 2.3 Obtain lower triangular matrix C from the Cholesky decomposition of Σ_i
   - 2.4 Check if candidate matrix $A_m = CZ_W$ satisfies the sign restriction
   - 2.5 Retain A_m if it does, discard if not.
   - 2.6 Repeat steps **2.1** to **2.5** 100 times

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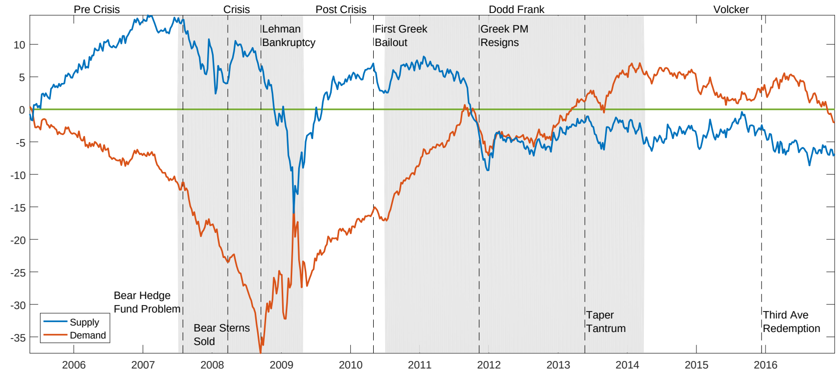
   2.6 Repeat steps **2.1** to **2.5** 100 times
3. Repeat steps **1** and **2** 100 times to obtain the posterior distribution of structural parameters and shocks.

Liquidity Supply and Demand Shocks

Pointwise mean of the cumulative sum of structural shocks, $\sum_{j=0}^{t} v_j$



Liquidity Supply and Demand Shocks: IG

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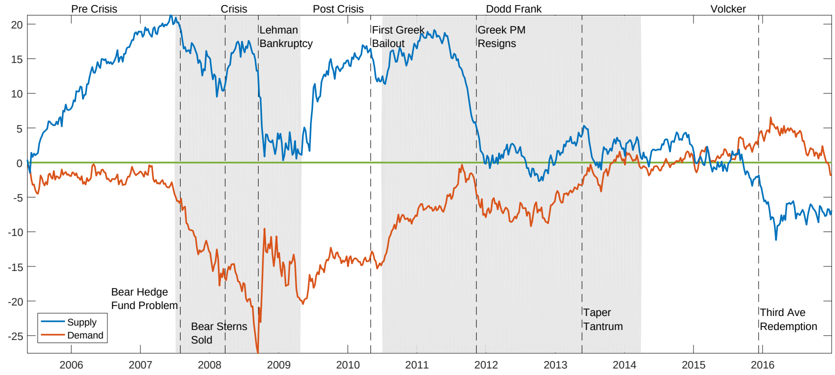
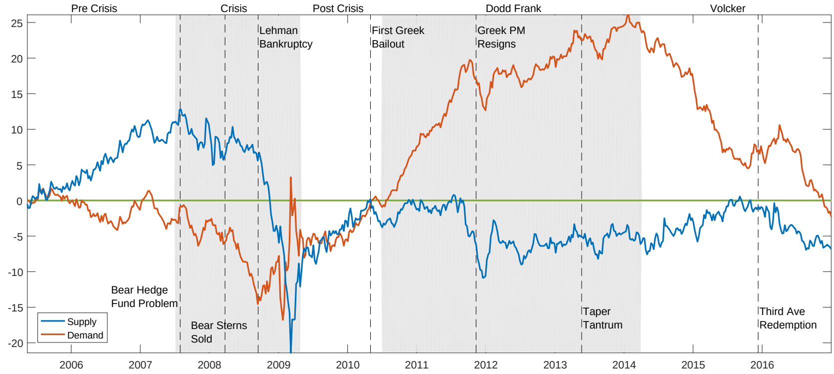


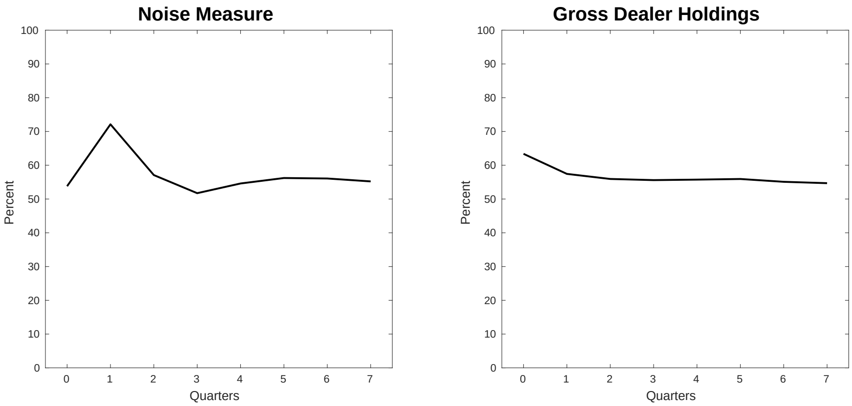
Liquidity Supply and Demand Shocks: HY

Pointwise mean of the cumulative sum of structural shocks, $\sum_{j=0}^{t} v_j$



Forecast Error Variance Decomposition

Fraction of variance of ξ_t explained by a supply shock.



Attributing Supply Shocks

To understand the drivers of supply shocks, regress shocks to known instruments.

$$v_t = b_1 \varepsilon_t^{VIX} + b_2 |FLOW_t| + b_{3t} \Delta ISSUE_t + b_4 HYSHARE_t + b_5 \varepsilon_t^{CAP} + b_6 \varepsilon_t^{TED} + b_7 R_{t-1} + u_t.$$

- ε_t^{VIX} : Innovation to VIX
- $FLOW_t$: Mutual fund flow to US domestic IG mutual funds
- $ISSUE_t$: Total face values of new issues
- $HYSHARE_t$: Share of HY bonds among new issues
- ε_t^{CAP} : Innovation to bank holding company capital (He, Kelly and Manela (2017))
- ε_t^{TED} : Innovation to TED spread
- R_{t-1} : Lagged return on the corporate bond index

Attributing Supply Shocks

VIX	IGFLOW	dISSUE	HYSHRE	CAP	TED	RET	R2
-0.12							0.02
(-2.79)							
	-0.01						0.00
	(-0.36)						
		0.12					0.02
		(2.77)					
			-0.08				0.01
			(-2.19)				
				0.16			0.03
				(3.23)			
					-0.12		0.02
					(-3.21)		
						0.01	0.00
						(0.15)	
0.01	-0.02	0.11	-0.04	0.16	-0.11	0.01	0.06
(0.25)	(-0.62)	(2.93)	(-1.06)	(2.72)	(-3.16)	(0.28)	

Attributing Demand Shocks

VIX	IGFLOW	dISSUE	HYSHRE	CAP	TED	RET	R2
0.10							0.01
(1.61)							
	0.05						0.00
	(1.90)						
		0.04					0.00
		(1.19)					
			0.00				0.00
			(0.07)				
				-0.07			0.01
				(-1.22)			
					0.07		0.01
					(1.67)		
						-0.04	0.00
						(-0.83)	
0.07	0.06	0.05	0.00	-0.03	0.06	-0.03	0.01
(1.17)	(2.02)	(1.26)	(0.08)	(-0.50)	(1.51)	(-0.68)	

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- Our measures are not affected by i), and we can disentangle ii) and iii).

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- Liquidity risk is priced in cross-section of stocks and corporate bonds.
- Existing liquidity measures reflect i) information asymmetry, ii) dealers' willingness to supply liquidity, and iii) investors' demand for liquidity.
- Our measures are not affected by i), and we can disentangle ii) and iii).
- Specifically, run time-series regression of returns on bond k over the 3-year rolling window,

$$R_{k,t} = b_0 + \beta_{k,s} v_t^s + \beta_{k,d} v_t^d + \varepsilon_{k,t}.$$

- We sort bonds based on their liquidity supply and demand betas into 5 portfolios.
- We report value-weighted average returns and factor alphas by running regressions,

$$R_{p,t} - R_{f,t} = \alpha_p + \sum^{J} \beta_{p,j} f_{j,t} + \eta_{p,t}$$

Corporate Bond Returns Sorted on $\beta_{k,s}$

	Low	2	3	4	High	H-L
Average Excess Returns						
$E\left[R^e_{p,t}\right]$	0.24	0.30	0.40	0.56	0.82	0.58
$tE\left[R^e_{p,t}\right]$	(1.54)	(2.69)	(3.25)	(3.39)	(2.64)	(2.64)
Fama-French 5 Factor Model + TERM + DEF						
α_p	-0.08	0.09	0.18	0.30	0.49	0.57
$t\left(\alpha_p\right)$	(-0.69)	(1.18)	(1.97)	(2.07)	(2.10)	(3.23)
Bai, Bali and Wen 4 Factor Model						
α_p	-0.23	-0.06	0.00	0.03	0.22	0.45
$t\left(\alpha_p\right)$	(-3.21)	(-1.98)	(0.03)	(0.59)	(2.50)	(3.30)
He, Kelly and Manela 2 Factor Model						
α_p	0.09	0.20	0.30	0.42	0.53	0.44
$t\left(\alpha_p\right)$	(0.54)	(1.55)	(2.04)	(2.34)	(1.96)	(2.37)

Corporate Bond Returns Sorted on $\beta_{k,s}$

Average characteristics of bonds:

	Low	2	3	4	High
β_s	-2.92	-0.98	-0.26	0.65	4.43
Maturity (years)	13.8	7.3	5.8	6.7	8.2
Size (mil. USD)	821.0	852.1	871.8	808.5	768.4
Age (years)	6.07	5.76	5.93	6.27	6.84
Roll (%)	1.01	0.63	0.58	0.75	1.20
IRC (%)	0.72	0.53	0.51	0.60	0.87
Fraction of Credit Ratings					
Aa+	10%	11%	11%	6%	2%
A	38%	42%	38%	30%	20%
Baa	31%	34%	37%	40%	31%
HY	20%	13%	13%	22%	45%

Corporate Bond Returns Sorted on $\beta_{k,d}$

	Low	2	3	4	High	H-L
Average Excess Returns						
$E\left[R^e_{p,t}\right]$	0.85	0.57	0.37	0.30	0.36	-0.48
$tE\left[R^e_{p,t}\right]$	(3.65)	(4.01)	(3.22)	(2.24)	(1.67)	(-2.91)
Fama-French 5 Factor Model + TERM + DEF						
α_p	0.54	0.35	0.17	0.06	0.02	-0.52
$t\left(\alpha_p\right)$	(2.34)	(2.62)	(1.70)	(0.60)	(0.15)	(-2.22)
Bai, Bali and Wen 4 Factor Model						
α_p	0.28	0.13	-0.02	-0.14	-0.18	-0.46
$t\left(\alpha_p\right)$	(2.31)	(1.79)	(-0.99)	(-1.88)	(-2.18)	(-2.30)
He, Kelly and Manela 2 Factor Model						
α_p	0.66	0.46	0.27	0.18	0.15	-0.51
$t\left(\alpha_p\right)$	(3.02)	(3.23)	(2.12)	(1.05)	(0.58)	(-2.33)

Corporate Bond Returns Sorted on $\beta_{k,d}$

Average characteristics of bonds:

	Low	2	3	4	High
β_d	-4.06	-0.78	0.04	0.80	3.20
Maturity (years)	8.2	6.5	5.8	8.0	13.4
Size (mil. USD)	688.8	798.7	885.1	878.5	872.6
Age (years)	6.74	6.22	5.93	5.81	6.17
Roll (%)	1.14	0.66	0.56	0.68	1.11
IRC (%)	0.81	0.56	0.49	0.56	0.79
Fraction of Credit Ratings					
Aa+	2%	7%	11%	12%	9%
A	17%	33%	40%	40%	37%
Baa	32%	38%	37%	36%	30%
HY	46%	21%	11%	12%	22%

Fama-MacBeth Regression of Monthly Bond Returns

q	$\beta_{k,s}$	$\beta_{k,d}$	Liq	Roll	Mat	Size	A	Baa	HY
Panel A: Dealer Balance Sheet									
0.16									
(1.72)									
0.09				0.28	0.02	0.07	-0.28	-0.23	-0.09
(1.20)				(2.90)	(0.36)	(1.91)	(-3.45)	(-2.69)	(-0.35)
Panel B: Supply and Demand Risk Premiums									
	0.35								
	(3.06)								
	0.23			0.27	0.11	0.06	-0.21	-0.18	0.08
	(2.89)			(3.48)	(1.81)	(1.70)	(-2.91)	(-2.27)	(0.54)
		-0.17							
		(-2.00)							
		-0.15		0.27	0.09	0.07	-0.20	-0.17	0.13
		(-2.26)		(3.48)	(1.55)	(1.86)	(-2.87)	(-2.05)	(0.84)

Fama-MacBeth Regression of Monthly Bond Returns

q	$\beta_{k,s}$	$\beta_{k,d}$	Liq	Roll	Mat	Size	A	Baa	HY
Panel C: With Amihud (2002) Measure									
	0.33		-0.18						
	(3.02)		(-1.25)						
	0.23		-0.13	0.24	0.13	0.07	-0.20	-0.20	0.02
	(2.93)		(-1.09)	(3.59)	(2.32)	(2.09)	(-2.93)	(-2.56)	(0.14)
		-0.13	-0.08						
		(-1.81)	(-0.58)						
		-0.15	-0.08	0.26	0.11	0.07	-0.20	-0.19	0.06
		(-2.29)	(-0.65)	(3.65)	(1.90)	(2.22)	(-2.99)	(-2.45)	(0.45)

Predicting Bond Index Returns

We examine whether the dealer's capital commitment predicts bond index returns, depending on the major driver of the capital commitment.

$$
\begin{aligned}
R_{t+h} &= b_0 + b_1 q_t + cX_t + \nu_{t+h}, \\
R_{t+h} &= b_0 + b_1 D_t q_t + b_2 (1 - D_t) q_t + cX_t + \nu_{t+h}
\end{aligned}
$$

where

$$
D_t = \begin{cases} 1 & \text{if } \left|\sum_{m=1}^{13} v_{t-13+m}^d\right| > \left|\sum_{m=1}^{13} v_{t-13+m}^s\right|, \\ 0 & \text{otherwise.} \end{cases}
$$

Idea: The capital commitment predicts returns when it is driven by supply shocks, not demand shocks.

Predicting Bond Index Returns

Horizon (weeks)	1	4	13	26	52
Panel A: Unconditional Forecasting Regressions					
q	0.18	0.59	-0.52	-2.98	-8.48
t-stat	(0.49)	(0.31)	(-0.11)	(-0.30)	(-0.69)
R^2	0.00	0.00	0.00	0.01	0.04
Panel B: Conditional Forecasting Regressions					
qD	0.44	2.57	6.17	7.29	5.31
t-stat	(0.72)	(0.94)	(1.33)	(1.21)	(0.55)
$q(1-D)$	-0.04	-1.36	-7.24	-14.18	-23.48
t-stat	(-0.11)	(-0.73)	(-2.18)	(-1.50)	(-2.40)
R^2	0.01	0.07	0.19	0.17	0.18

Conclusion

- We estimate liquidity supply and demand by jointly analyzing liquidity price and quantity:
  - Price: Noise measure in corporate bond yields
  - Quantity: Dealer gross positions
- No need for ad-hoc instruments
- Our liquidity measures are not affected by i) changing roles of dealers, ii) changing chracteristics of realized trades, iii) anything specific to issuers, such as information asymmetry
- Liquidity supply and demand carry different price of risks.
  - In cross section of bonds, supply and demand betas have risk premiums with opposite signs
  - In time-series data, dealer's capital commitment predicts returns only when it is driven by supply shocks

Liquidity Contagion

- Gromb and Vayanos (2002, 2017): A dealer loses money in one market $\Rightarrow$ Reduce liquidity supply in the other market (Collateral Constraint)
- Ellul, Jotikasthira and Lundblad (2012): Investment-grade bond and high yield bond markets are segmented

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- Question: Does an increase in noise in one market leads to reduced liquidity supply in the other?
- VAR with a state vector

$$Y_t^{HY \to IG} = \begin{pmatrix} p_t^{IG} & q_t^{IG} & p_t^{HY} \end{pmatrix}'$$

- Sign restrictions

$$\begin{pmatrix} \xi_t^{p,IG} \\ \xi_t^{q,IG} \\ \xi_t^{p,HY} \end{pmatrix} = \underbrace{\begin{pmatrix} - & + & 0 \\ + & + & 0 \\ ? & ? & + \end{pmatrix}}_{A} \begin{pmatrix} v_t^s \\ v_t^d \\ v_t^{HY} \end{pmatrix}$$

- v_t^{HY} : A shock to the high-yield bond market that is uncorrelated with investment grade market on impact.

Liquidity Contagion

- Conversely, we can also run a VAR with a state vector

$$Y_t^{IG \to HY} = \begin{pmatrix} p_t^{HY} & q_t^{HY} & p_t^{IG} \end{pmatrix}'$$

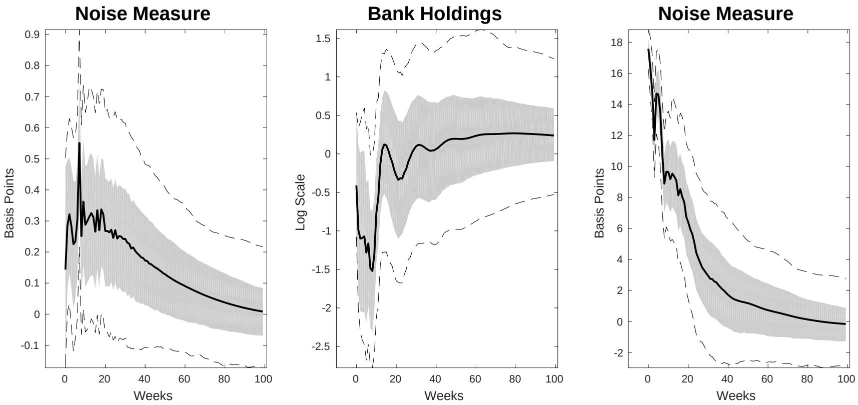
- Sign restrictions

$$\begin{pmatrix} \xi_t^{p,HY} \\ \xi_t^{q,HY} \\ \xi_t^{p,IG} \end{pmatrix} = \underbrace{\begin{pmatrix} - & + & 0 \\ + & + & 0 \\ ? & ? & + \end{pmatrix}}_{A} \begin{pmatrix} v_t^s \\ v_t^d \\ v_t^{IG} \end{pmatrix}$$

- v_t^{IG} : A shock to the investment grade bond market that is uncorrelated with high-yield market on impact.

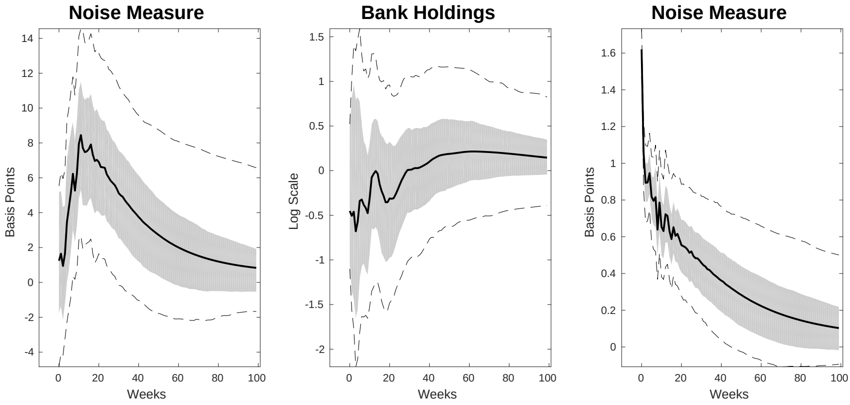
Contagion from HY to IG Markets

- $\sigma\left(\xi_t^{p,IG}\right) = 1.7$ bps $\Rightarrow$ weak contagion.



Contagion from IG to HY Markets

- More visible reaction in noise in the HY market



- IG market is larger than HY market, and thus contagion **from** IG market is more important.