

Estimating a Model of Decentralized Trade with Asymmetric Information

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Motivation

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- Fundamental risk: Will bond issuer default?
- Information friction: Some market participants know more than others
- Search friction: market participants must search to find trading partner
- Recent developments have decreased search cost:
 - Electronic trading
 - RFQ systems
 - Regulation (e.g. MiFID II): min. proportion of trade on exchange
- Are lower search cost beneficial?

This paper

- Focus on **liquidity**: bid-ask spread
- Spread arises due to adverse selection
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 - Lower search cost \rightarrow More liquidity trades \rightarrow Adverse selection less severe \rightarrow Spreads decline
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- Which effect dominates depends on parameter values
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- Question: Where are real financial markets?
- Result: Liquidity improves (first effect dominates)

Related literature

- Theoretical literature on trading in OTC markets is vast
 - Seminal paper: Duffie, Garleanu, and Pedersen (2005)
 - Survey: Weill (2020)
 - This paper: Uses model from Lester, Shourideh, Venkateswaran, and Zetlin-Jones (2018)
 - LSVZ model unique in this literature for looking jointly at search and information frictions
- Empirical analysis of OTC markets
 - Dealer networks: Li and Schurhoff (2019), Hagstromer and Menkveld (2019)
 - Electronic trading: O'Hara and Zhou (2019), Vogel (2019)
 - Transaction costs: Edwards, Harris, and Piwowar (2007), Bessembinder, Maxwell, and Venkataraman (2006)
 - None of these papers jointly consider a search friction and asymmetric information
- Structural estimation of a model of a search market
 - Eckstein and Wolpin (1990), Carrillo (2012), Gavazza (2016), Feldhutter (2012)
 - This paper: Similar technique but focus on corporate bond market

Data

- U.S. corporate bond market
- Mergent FISD database: characteristic information
- Eliminate non-standard bonds (convertible, variable coupon, asset backed, perpetual, private placed, etc.)
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- Period: October 2015 to October 2019
- Eliminate D2D trades
- Cleaning procedure: Dick-Nielsen (2014)
- ~ 46 million transactions

Summary statistics

	Time to maturity			
	< 1 year	1-3 years	3-10 years	> 10 years
Mean amount outstanding	660m	651m	589m	514m
Median amount outstanding	500m	500m	400m	350m
Mean trade size	615k	421k	428k	789k
Median trade size	30k	25k	25k	50k
Mean no. of trades per week	16	16	16	7
Median no. of trades per week	8	8	7	3

Table: Summary statistics on the trading activity in investment grade bonds

The Model

Environment:

- Two states of the world: $j \in \{h, l\}$
- A single risky asset with fundamental value v_j , $v_h > v_l$
- Time $t = 1, 2, \dots$, game ends every period with chance $1 - \delta$

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Players:

- A continuum of traders (investors) and dealers with mass 1 each.
- All agents are risk-neutral and live forever
- Dealers can take unrestricted positions in the asset
- Traders are either “owners” or “non-owners”

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Payoffs:

- When game ends asset pays v_j .
- For investor i the asset also pays flow payoff of $\omega_t + \epsilon_{it}$ where $\omega_t \stackrel{iid}{\sim} \mathcal{N}(0, \sigma_\omega^2)$, $\epsilon_{it} \stackrel{iid}{\sim} \mathcal{N}(0, \sigma_\epsilon^2)$
(denote cdfs by F and G respectively)

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Timing:

1. Game ends with probability $1 - \delta$.
2. Each investor meets a dealer with probability π .
3. The dealers then quote a bid and ask price.

$$A_t = \mathbb{E}_{j,\omega}(V|I_t, \text{buy at } A_t), \quad B_t = \mathbb{E}_{j,\omega}(V|I_t, \text{sell at } B_t)$$

4. Investor decides: trade or walk away.
Threshold rule: buy if $\epsilon > \bar{\epsilon}_j$, sell if $\epsilon < \underline{\epsilon}_j$, walk away otherwise;
Thresholds depend on prices, aggregate shock, and reservation value $R_{j,t}$
5. Dealers observe aggregate trading. Equivalent to observing $R_{j,t} + \omega_t$
6. Dealers update using Bayes' rule.

Methodology

- Simulated Method of Moments (SMM) – McFadden (1989), Pakes and Pollard (1989)
- Principle as in GMM: Match model moments and data moments
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- The SMM estimator is

$$\hat{\beta} = \arg \min_{\beta} \left(\frac{1}{S} \sum_{s=1}^S m_s(\beta) - m_D \right)' W \left(\frac{1}{S} \sum_{s=1}^S m_s(\beta) - m_D \right)$$

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- To compute SE use

$$Avar(\hat{\beta}) = \left(1 + \frac{1}{S} \right) \left[\frac{\partial m_s(\hat{\beta})'}{\partial \beta} W \frac{\partial m_s(\hat{\beta})}{\partial \beta} \right]^{-1}$$

Methodology – Calibration

- Some parameters are not identified by the data. Set them as follows
 - One model period = one trading week
 - Continuation chance: $\delta = 0.99$.
 - Initial belief: $\mu_0 = 0.9$.
 - $v_h = 1$ (bond does not default)
 - $v_l = 0$ (bond defaults)
- Remaining parameters to estimate via SMM: $\{\pi, \sigma_\omega, \sigma_\epsilon\}$.

Methodology – Moments

1. The average spread. [▶ Computation](#)
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3. The fraction of investors who traded.
4. The trade imbalance.
5. The variance of the price.
6. The price impact.

Results

High yield	< 1 year	1-3 years	3-10 years	> 10 years
π	0.23 (0.06)	0.15 (0.01)	0.23 (0.02)	0.22 (0.01)
σ_ω	1.28 (0.36)	1.05 (0.08)	0.50 (0.03)	0.43 (0.02)
σ_ϵ	10.43 (2.56)	8.55 (2.46)	2.91 (0.35)	1.65 (0.15)

Investment grade	< 1 year	1-3 years	3-10 years	> 10 years
π	0.26 (0.13)	0.17 (0.03)	0.18 (0.02)	0.20 (0.01)
σ_ω	2.14 (1.41)	2.10 (0.31)	0.99 (0.09)	0.57 (0.04)
σ_ϵ	15.13 (4.64)	10.99 (2.22)	4.42 (0.51)	1.83 (0.14)

Table: Results for the non-stationary version of the model. Standard errors in parentheses.

Counterfactual analysis

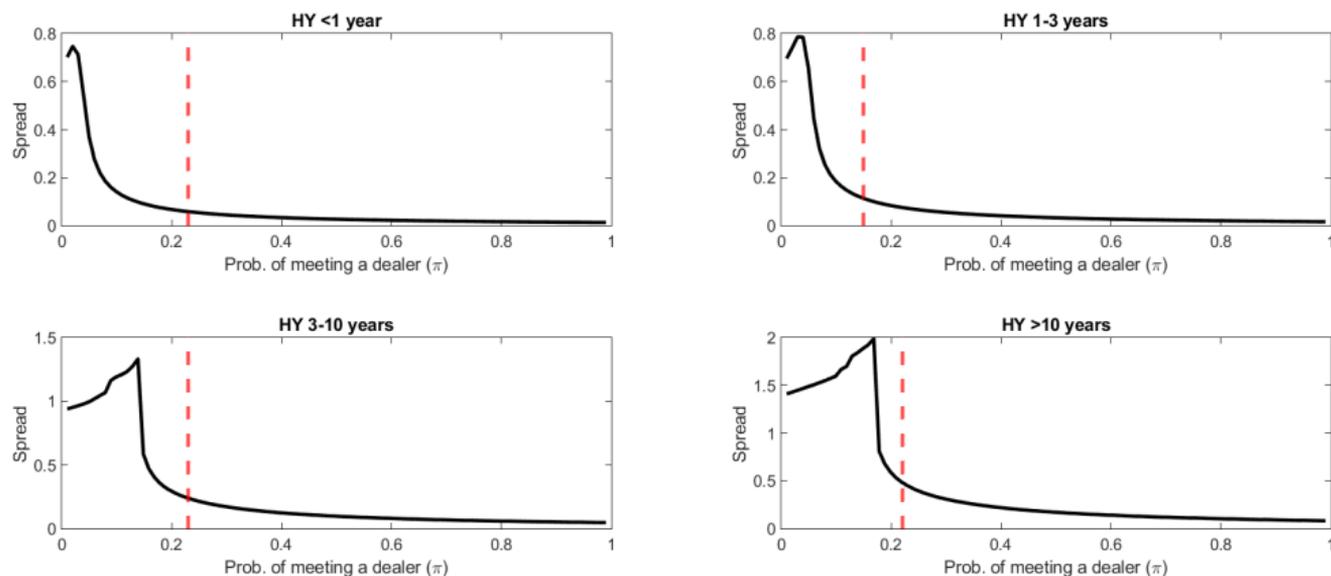


Figure: Sensitivity analysis: Model-implied spreads for different values of π . All other parameters are fixed at their estimated value. The vertical line is drawn at the SMM estimate for π .

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Thank you!

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- Dataset only contains *transactions*, no order book!
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- Idea: Pre-arranged trades where dealer acts as middleman only
- Appear in dataset as pair of transactions in same security with same volume within 15 minutes of each other.
- The IRT measure is $P_{max} - P_{min}$.

Methodology – Spreads

By trade size	< 25k	25k – 100k	100k – 500k	> 500k
HY	47	51	28	13
IG	53	53	26	11

By Maturity	< 1 year	1-3 years	3-10 years	> 10 years
HY	15	27	48	73
IG	13	23	46	77

Over time	15Q4 - 16Q3	16Q4 - 17Q3	17Q4 - 18Q3	18Q4 - 19Q3
HY	52	44	39	36
IG	57	49	44	38

Table: “Imputed Roundtrip” spreads for the corporate bonds in my sample. Values are in USD cents.