Discussion of Hennig (2020)

“Estimating a Model of Decentralized Trade with Asymmetric Information”

Sangmin S. Oh

Modelling with Big Data & Machine Learning 2020

Overview

- Very interesting paper
- Exposition is very clear – I learned a lot while reading.
- Main finding: decrease in trading frictions improves liquidity but slows down learning.

My Discussion

- Key Idea & Interpretation
- Comments

Key Idea & Interpretation

Original Model (LSVZ, 2018): Two key sources of illiquidity

1. Trading (search) frictions: investors trade infrequently, dealers have market power
2. Informational frictions: investors know more about asset than dealers

   $\Rightarrow$ Dealers learn over time from market-wide trading activity

Author's Version: A simplified version where he sets $\alpha_c = 1$, i.e.

$$\alpha_c = 1 - \alpha_m = 1 - \frac{p_1}{\pi} = 1$$

where α_m is the probability of meeting with one dealer, conditional on meeting with $n \geq 1$ dealers and p_n is the probability that a trader meets n dealers.

- Essentially, this is retaining a fraction of the trading friction by setting $p_1 = 0$.
- In the original model, p_0 and p_1 are sufficient statistics that summarize trading frictions.

Key Idea & Interpretation

Estimation: Simulated Method of Moments (SMM)

- Author follows a standard implementation
- Three parameters: meeting probability and liquidity shocks – $\{\pi, \sigma_\omega, \sigma_\epsilon\}$
- Six moment conditions

Main Takeaways:

1. Increase π by 20%: A decrease in trading frictions prompts a decraese in the spreads
2. Examine convergence of price paths $\Rightarrow$ Slowdown in learning

Comment #1: What are we losing from the simplification?

- In the original LSVZ-2018, the dealer chooses A_t (ask) and B_t (bid) prices, which yields in equilibrium:

$$A_t = \mathbb{E}_j v_j + \underbrace{\frac{1-\mathbb{E}_{j,\omega}\left[G\left(\bar{\varepsilon}_{j,t}\right)\right]}{\mathbb{E}_{j,\omega}\left[g\left(\bar{\varepsilon}_{j,t}\right)\right]}}_{\text{market power}} + \underbrace{\mu_t(1-\mu_t)(v_h - v_l)\frac{\mathbb{E}_{\omega}\left[g\left(\bar{\varepsilon}_{h,t}\right)-g\left(\bar{\varepsilon}_{l,t}\right)\right]}{\mathbb{E}_{j,\omega}\left[g\left(\bar{\varepsilon}_{j,t}\right)\right]}}_{\text{asymmetric information}}$$

$$B_t = \mathbb{E} v_j - \frac{\mathbb{E}_{j,\omega}\left[G\left(\underline{\varepsilon}_{j,t}\right)\right]}{\mathbb{E}_{j,\omega}\left[g\left(\underline{\varepsilon}_{j,t}\right)\right]} - \mu_t(1-\mu_t)(v_h - v_l)\frac{\mathbb{E}_{\omega}\left[g\left(\underline{\varepsilon}_{l,t}\right)-g\left(\underline{\varepsilon}_{h,t}\right)\right]}{\mathbb{E}_{j,\omega}\left[g\left(\underline{\varepsilon}_{j,t}\right)\right])}.$$

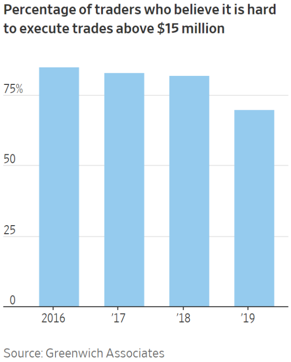
- Assuming "competitive" version implies

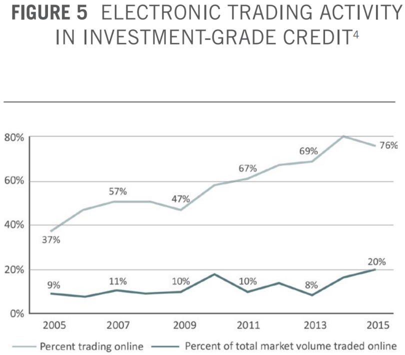
$$A_t = \frac{\mathbb{E}_{j,\omega}\left(v_j\left(1-G\left(\bar{\epsilon}_{j,t}\left(\mu,\omega\right)\right)\right)\right)}{\mathbb{E}_{j,\omega}\left(1-G\left(\bar{\epsilon}_{j,t}\left(\mu,\omega\right)\right)\right)}, \quad B_t = \frac{\mathbb{E}_{j,\omega}\left(v_j G\left(\underline{\epsilon}_{j,t}\left(\mu,\omega\right)\right)\right)}{\mathbb{E}_{j,\omega}\left(G\left(\underline{\epsilon}_{j,t}\left(\mu,\omega\right)\right)\right)}$$

- The bid-ask spread arises due to the adverse selection faced by dealers, but interesting information on levels is lost.

Comment #2: More reduced form evidence

- Can we see more reduced-form evidence before jumping to the estimation?





- Examples from Nasdaq, or earlier corporate bonds trading?

Comment #3: Framing the Paper

- Most of the interesting results come from the counterfactual exercise.

  $\Rightarrow$ I would put the counterfactual exercise at the center of the paper.
- Bolstering the motivation of the paper
  - MiFID II is only mentioned twice in the paper – Additional institutional details can help.
- Is the spread more interesting than welfare as a final outcome variable?
- Useful reference: Plante (2020): “Should Corporate Bond Trading Be Centralized?”

Comment #4: Relaxing the Restrictions on the Model

Distribution of the shocks:

- Model assumes that the liquidity shocks are normally distributed with CDFs $F(\cdot)$ and $G(\cdot)$
- How would the model fare with an asymmetric distribution? (e.g. power law)
  - Focus on extreme illiquid events: Wu (2015), Anthonisz and Putnins (2016)
- The original paper also covers the uniform distribution case, which is worth exploring.

Additional Parameter for estimation:

- Author currently sets $\alpha_c = 1$ in the Lester et al. (2018) paper.
- Why not estimate the full model and estimate α_c from the data?

Minor Comments

Implementation Details:

- For price-based moments (#4 and #5), why not use mid-price?

Missing Citations:

- Pros and cons of centralizing corporate bond trades: Plante (2020)

Additional Results:

- Would be useful to see the full-sample results as well and not only the sub-samples!

Conclusion

- Interesting paper with high-quality exposition
- Potential to make it more impactful by reframing + additional results