Intermediary Market Power and Capital Constraints

Jason Allen Milena Wittwer

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[0] The views in this paper do not reflect those of the Bank of Canada.

Motivation

What moves asset prices?

- Intermediary asset pricing: capital/constraints of financial intermediaries

  E.g., He and Krishnamurthy (2012, 2013); Brunnermeier and Sannikov (2014)

- Intermediaries, e.g., Bank of America, Royal Bank of Canada
  1. Face capital constraints
  2. Have market power

Capital constraints

Basel III leverage ratio (LR)

- Requires banks to hold sufficient equity capital
- Major constraint on bank activity (Jerome Powell)

Leverage Ratio Runs Counter to Policy Objectives (Wall Street Journal, 2016)

Washington Wants to Weaken Bank Rules. Not Every Regulator Agrees. (New York Times, 2018)

US banks push Fed for extension of Covid capital relief (Financial Times, 2021)

Geithner stresses need for SLR reform (Risk.net, 2022)

- This paper focuses on the cost induced by constraints; abstracts from benefits

Contribution

Examines how **capital constraints** affect asset prices in a framework that allows for intermediary **market power**

- **Theoretically**
  - (today) Uniform price auction with continuous demand
  - Capital-constrained dealers have market power
- **Empirically** for the Canadian primary market for government debt
  - Discriminatory price auction where demand is a step function
  - Why? Dealers submit demand curves and balance sheet information
  - How? Policy change of Basel III leverage ratio

Model: Environment

Goods

- An asset pays per unit return $R \sim N(\mu, \sigma)$
- Cash (numeraire)

Players

- $N > 2$ dealers have **market power** if $N < \infty$
- Before bidding, dealer i has θ_i of capital, owns $z_i = 0$ of the asset

Information structure

- Supply of the asset is unknown: $\boldsymbol{Q} \sim F_Q$ on $[\underline{Q}, \overline{Q}]$
- Dealer's balance sheet is private information: $\boldsymbol{\theta_i} \sim F_\theta$, iid across i

Model: Dealer problem

- Each dealer chooses demand schedule $p_i(\cdot, \theta_i) : \mathbb{R}^+ \to \mathbb{R}^+$ to maximize

$$\mathbb{E}\left[1 - \exp\left(-\rho\omega_i(\boldsymbol{q_i^c}, \boldsymbol{P^c})|\theta_i\right]$$

with $\omega_i(\boldsymbol{q_i^c}, \boldsymbol{P^c}) = \boldsymbol{q_i^c R} - \boldsymbol{P^c q_i^c}$ and $\rho > 0$

subject to: $\kappa\mathbb{E}[\boldsymbol{P^c q_i^c}|\theta_i] \leq \theta_i$ where $\kappa > 0$ (capital constraint)

- Market clears at P^c such that $\sum_i q_i^c = Q$, and dealer i wins $q_i^c = p_i^{-1}(P^c, \theta_i)$

Model: Contribution

Challenge

- Standard approaches for solving for an equilibrium do not work when bidders (here dealers) face **outcome-dependent constraints** (here capital constraints)

Methodological contribution to auction literature (Kyle (1989), Wilson (1989))

1. Derive necessary conditions for Bayesian Nash Equilibria
2. Show there is no linear equilibrium when dealers have private information
3. Derive unique sym. linear equilibrium when dealers only face supply uncertainty

Model: Equilibrium condition

In any Bayesian Nash Equilibrium dealer i chooses amount q at price p is such that:

$$\text{marginal utility} \;=\; \text{marginal disutility}$$

1. No capital constraint & perfect competition:

$$\mu - \rho\sigma q = p$$

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$$\mu - \rho\sigma q = (1 + \lambda_i \kappa)p$$

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$$\mu - \rho\sigma q = (1 + \lambda_i \kappa) p$$

3. With capital constraint & market power

$$\mu - \rho\sigma q = (1 + \lambda_i \kappa)[p + \Lambda_i(\vec{\lambda}) q],$$

Model: Equilibrium condition

In any Bayesian Nash Equilibrium dealer i chooses amount q at price p is such that:

$$\frac{v_i(q)}{1 + \lambda_i \kappa} = p + \Lambda_i(\vec{\lambda})q$$

where $v_i(q) = \mu - \rho\sigma q$, and $\Lambda_i(\vec{\lambda})$ is the dealer's "probabilistic" price impact.

Model: Equilibrium condition

In a Bayesian Nash Equilibrium in an auction with constraints dealers bid as if they were competing in an auction w/o constraints in which their willingness to pay was

$$\tilde{v}_i(q) = \frac{v_i(q)}{1 + \lambda_i \kappa} \text{ instead of } v_i(q).$$

Canadian Treasury auctions

Environment

- 8 dealers buy most debt; each faces Basel III capital constraint
- Auctions are discriminatory price; demand curves are step-functions

Bidding data of all 176 government bond auctions (01/01/2015–02/01/2021)

- Who bids (ID), winning and losing bids

Trade prices of the secondary market (Jan. 2017 to Feb. 2021)

Estimation: Overview

Goal

1. Shadow **costs of the capital constraint** for each dealer i in each auction t ($\lambda\kappa_{it}$)
2. Degree of **risk aversion** of dealers (ρ)

How?

- Estimate how much each dealer is willing to pay (WTP) in each auction
- Leverage temporary exemption of government bonds from Basel III constraint

Estimation: Willingness to pay (WTP)

The model predicts the following WTP of dealer i in auction t for amount q_{tik}:

$$\tilde{v}_{tik} = \zeta_{ti} - \boldsymbol{\beta_{ti}} \times \sigma_t \times q_{tik} \text{ with } \boldsymbol{\beta_{ti}} = \frac{\rho_m}{1 + \lambda\kappa_{ti}}$$

- $\zeta_{ti} = f_t(\theta_{ti})$ is the effect of private information θ_{ti}
- σ_t is return volatility
- $\rho_m \geq 0$ measures the degree of risk aversion for a bond with maturity m
- $\lambda\kappa_{ti} \geq 0$ represent the shadow costs of capital

Estimation

(1) **Get willingness to pay, $\tilde{v}_{tik}$, that rationalized observed bids, $\{p_{tik}, q_{tik}\}_{k=1}^{K_{ti}}$**

– From equilibrium conditions:

$$p_{tik} = \tilde{v}_{tik} - \underbrace{\frac{\Pr(p_{tik+1} \geq \boldsymbol{P_t^*} | \theta_{it})}{\Pr(p_{tik} > \boldsymbol{P_t^*} > p_{tik+1} | \theta_{it})}}_{shading}$$

– Estimate $\Pr(\cdot|\theta_{ti})$ following Allen, Hortacsu, Richert, and Wittwer (2023)

Estimation

(2) **Estimate the slope coefficients, β_{ti}, using variation across steps k**

$$\tilde{v}_{tik} = \zeta_{ti} - \beta_{ti} \times \sigma_t \times q_{tik} + \epsilon_{tik}$$

- $\tilde{v}_{tik}$ is WTP in auction t of dealer i at step k (estimated)
- ζ_{ti} is an auction-dealer fixed effect
- σ_t is return volatility (observed)
- q_{tik} is quantity demanded in auction t of dealer i at step k (observed)
- ϵ_{tik} captures estimation error from resampling

graph

Estimation

Recall:

$$\beta_{ti} = \frac{\rho_m}{1 + \lambda \kappa_{ti}}$$

(3) **Separately identify the degree of risk-aversion and shadow costs**

- By comparing slopes in auctions around the two policy changes
- Assuming that risk-aversion is constant around each policy changes

graph

Estimates

- **The median degree of risk aversion is 0.006—low but not risk-neutral**
- Existing estimates in non-financial settings are similar, typically larger

  E.g., Bolotony and Vasserman (2023), Haefner (2023)

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- **Median shadow cost is 3.5%, which is sizable**
- Existing studies use spreads to capture balance sheet costs, find lower values

  E.g., Du et al. (2018; 2023); Siriwardane et al (2021)

Estimates: Trade-off

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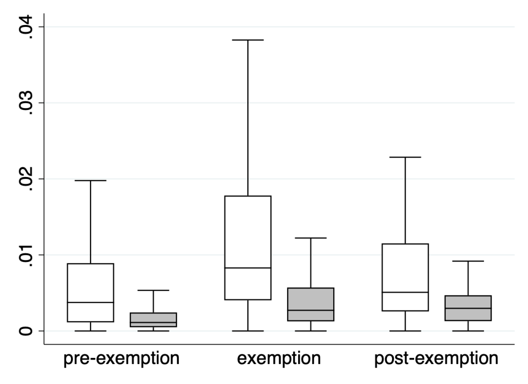
- Decreasing capital costs by 1%, increases price and price distortion by $\approx$ 3.4 bps

Conclusion

This paper

- Shows that dealer capitalization affects asset prices and market power—trade-off!
- Quantifies the effects with data on Treasury auctions

Figure: Slope coefficients of estimated value and observed bids



White boxplots show the distribution of the estimated slopes coefficients of the dealers' WTP across dealers and auctions. Gray shows slopes of bidding functions. Pre-exemption (2019q1–2020q1), exemption (2020q1–2021q4), post-exemption.

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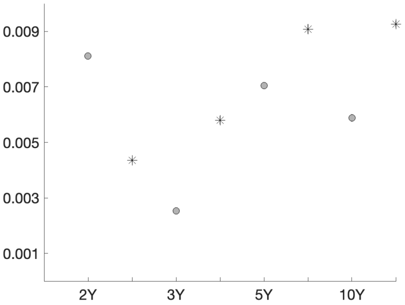
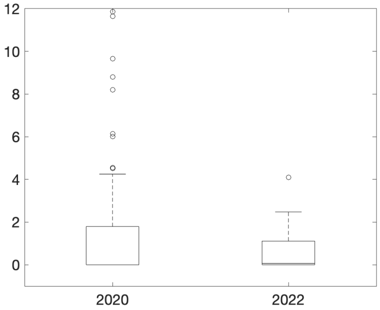


(A) Risk aversion



(B) Shadow costs

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