Intermediary asset pricing: Capital constraints and market power *

Jason Allen[+] and Milena Wittwer[§]

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Abstract

We study if and how the capitalization of financial intermediaries affects asset demand and prices in a framework that allows for intermediary market power. We show that weaker capital constraints lowers yields but raises markups due to market power. We test these predictions and calibrate the model with data on the Canadian primary market for government bonds, where we can link asset demand to balance sheet information of individual intermediaries. A counterfactual analysis shows that relaxing capital constraints can reduce bond yields but increases markups, each by 49%. This implies lower debt funding costs at an implicit cost of higher yield distortion.

Keywords: Financial intermediaries, market power, price impact, asset demand, asset pricing, government bonds, Basel III, capital requirements, leverage ratios

JEL: G12, G18, G20, D40, D44, L10

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1 Introduction

What moves asset prices is one of the oldest questions in finance. The intermediary asset pricing literature suggests that the prices of many assets depend not only on the preferences of households, but also on the equity capitalization of financial intermediaries, called dealers (e.g., Brunnermeier and Pedersen (2009); He and Krishnamurthy (2012, 2013); Brunnermeier and Sannikov (2014)). One reason is that dealers face capital constraints. At the same time, dealers enjoy market power in various markets settings, for instance in Treasury, Repo and Foreign exchange markets (as documented by Allen and Wittwer (2020); Huber (2022); Wallen (2022)). This stands in contrast to the traditional view in finance that markets are highly competitive, motivating the assumption of perfect competition in models of intermediary asset pricing.

We zoom in on the intermediary sector to study how dealer capitalization affects asset demand, and therefore prices, and quantify the effect in a framework that allows for dealer market power (as in Kyle (1989)). We first introduce a model in which strategic dealers face regulatory capital constraints to highlight how their asset-demand, and ultimately prices, are impacted by their degree of capitalization and market power. Then, we test and calibrate the model with data on Canadian Treasury auctions by leveraging regulatory changes during the COVID-19 pandemic.

In the model, dealers compete to buy multiple units of an asset that pays out an uncertain return in the future. They are risk averse and subject to a capital constraint. The market may clear via different auction formats, which represent primary auctions or exchanges. In the benchmark auction, each dealer submits a demand curve that specifies how much it is willing to pay for different units of the asset.[1] The market clears at the price at which aggregate dealer demand meets supply, and each dealer wins the amount it asked for at that price (uniform price auction).

We show that there is a unique linear equilibrium in which each dealer's demand depends on whether and how tightly the capital constraint binds. This is measured by the shadow cost of the capital constraint, i.e., the Lagrange multiplier. The main pre-

[1] In a traditional trade-setting, the auction would turn into a double auction, and the demand functions would represent packages of limit orders of small size (e.g., Duffie and Zhu (2017); Wittwer (2021)).

diction of the model is that demand (which map prices into quantities) becomes flatter when capital constraints are relaxed as it becomes cheaper to buy larger amounts of the asset. Unless supply adjusts, the market price increases.[2] At the same time, dealers distort the market price further away from the price that would arise if they were price-takers. This is a source of inefficiency, for instance, because distorted prices in the primary market may distort trading behavior and security allocation in the secondary market.

We use data on Canadian Treasury auctions to test and calibrate the model because of two attractive features. First, dealers submit entire demand curves. We can therefore observe whether dealer demand is flat or steep. Alternatively, we would need to aggregate individual demands from secondary market trades—which involves observing individual secondary market trades, and pooling data points over time and across market participants. Second, we can link the dealers' demand curves to balance sheet information, which is crucial for establishing a link between dealer demand and capitalization.

Our data combines bidding information on all regular Canadian Treasury auctions between January 2015 and February 2022 with balance sheet information of the eight largest dealers at the company holding level (following He et al. (2017)). We observe all winning and losing bids. Bids are expressed in yields to maturity which is the annualized interest rates that equate the prices with the present discount values of the bonds. This is why we conduct our empirical analysis with yields instead of prices. In addition, we see the Basel III Leverage Ratio (LR) of each dealer-bank, which is the Canadian equivalent to the Supplementary Leverage Ratio (SLR) in the U.S. It is reported quarterly, measures a bank's Tier 1 capital relative to its total leverage exposure, and must be above an institutional-specific regulatory threshold, which we also observe.

With the data, we gather evidence in favor of the model's predictions. For this, we

[2]The prediction that the asset price increases when the capital cost decreases is in line with He and Krishnamurthy (2012, 2013) and Brunnermeier and Sannikov (2014)'s prediction that leverage has a negative price of risk. In their models this is because a negative shock to the net worth (equity capital) of a dealer decreases its risk-bearing capacity. In our model, risk aversion is constant.

leverage that domestic government bonds were temporarily exempted from the LR to buffer against negative effects of the COVID-19 pandemic. Through the lenses of our model, this means that the capital constraint was temporarily lifted. An event study confirms that the demand of dealers who were more strongly affected by the policy change became flatter when the exemption period started, and steeper when it ended relative to the other dealers, as predicted by our model. In theory, this decreases the market yield but increases markups. Empirically, these effects are hard to identify.

We leverage our model to quantify by how much the market yield and markups change when the constraint is relaxed or tightened. To pin down the banks' degree of risk aversion and the shadow cost of the capital constraint, we first estimate how much bidders are willing to pay in each auction using estimation techniques from the auctions literature (introduced by Guerre et al. (2000); Hortaçsu and McAdams (2010); Kastl (2011)). Then we exploit that the willingness to pay of a dealer depends on market observable characteristics (such as market volatility), in addition to the degree of risk aversion and the shadow cost according to our theory. Therefore, we can identify these parameters from how the willingness to pay of a dealer changes around the policy changes.

We find that banks are close to risk-neutral. This is reassuring given that these are global banks who can diversity away most types of risk. At the same time, banks face sizable costs due to the capital constraint. The shadow cost parameters imply that the market yield and markups increase by 0.23%–0.49% if the shadow cost of the constraint increases by 1%. In comparison, estimates from regressing auction yields on LR—which we suspect to be upward biased due to endogeneity—imply that a 1% increase in LR increases the yield by roughly 0.57%–0.78%. This result provides some validation to the model, given that the elasticities are not dissimilar and the bias goes in the expected direction. Yet we do not use the regression information to estimate the model.

Our findings have valuable implications for government bond markets, which were under severe distress in March 2020. Globally, banking regulators took measures to facilitate central bank's ability to support financial intermediation activities. These measures made it cheaper for dealers to absorb the excess supply of government bonds

onto their balance sheets. Our counterfactual analyses reveals welfare benefits and costs: the relaxation of the LR led to a reduction in bond yields but an increase in markups of 23%–49%. This translates into higher auction revenues and thus savings for the government at an implicit cost of larger yield distortion.

Beyond implications for government bond markets, our evidence contributes to an ongoing debate in the asset pricing literature on whether, and if so how, capitalization of financial intermediaries affects asset prices (e.g., Adrian et al. (2014); He et al. (2017); Gospodinov and Robotti (2021)). We complement existing studies that rely on market-level data and proxy variables for intermediary costs by zooming in on one market in which we can observe the relationship between intermediary capitalization, demand and the market price. Since our model is not specific to the Canadian Treasury market, we conjecture that our findings generalize to many other financial markets in which financial institutions intermediate trade.

Related literature. Our main contribution is to explain and quantify how dealer capitalization affects asset demand and prices when dealers have market power.

This topic fits into an ample intermediary asset pricing literature that examines the impact of dealer capitalization (or leverage) on asset price behavior due to constraints on debt (e.g., Brunnermeier and Pedersen (2009); Pedersen and Gârleanu (2011); Adrian and Shin (2014); Moreira and Savov (2017); Elenev et al. (2021)), or constraints on equity (e.g., He and Krishnamurthy (2013, 2012); Brunnermeier and Sannikov (2014)).[3] Given our focus on banks, we follow He et al. (2017) and rely on equity constraints. Similar to models with balance sheet costs, issuing capital to fulfill the regulatory constraint is costly in our model (e.g., Andersen et al. (2019); Kondor and Vayanos (2019); He et al. (2022)).

The key difference to all these models is that we zoom in on the intermediary financial sector and allow dealers to impact prices as a result of market power in the tradition of Kyle (1989). The market clears via a multi-unit auction (as in Vayanos

[3]Earlier contributions include Bernanke and Gertler (1989); Aiyagari and Gertler (1999); Kyle and Xiong (2001); Xiong (2001); Gromb and Vayanos (2002) and Fostel and Geanakoplos (2008). See Geanakoplos (2009) for a literature survey on the relation between leverage and interest rates.

(1999); Vives (2011); Rostek and Weretka (2012); Malamud and Rostek (2017); Wittwer (2021)). Our innovation is to introduce a capital constraint and analyze its effect on market outcomes and market power.

Our empirical analysis adds to a growing literature on the relation between intermediary costs or constraints and asset prices (e.g., Adrian and Shin (2010); Ang et al. (2011); Adrian et al. (2014); He et al. (2017); Du et al. (2018); Check et al. (2019); Gospodinov and Robotti (2021); Haddad and Muir (2021); Baron and Muir (2022); Fontaine et al. (2022)). Most existing studies use market-level data, such as cross-sectional returns of different asset classes, and rely on proxy variables to capture intermediary costs, such as the VIX or aggregate capital holdings.

We zoom in on one market in which we can link dealer demand with balance sheet information to establish a direct relationship between dealer capitalization and asset demand, and identify a mechanism through which capital affects asset prices. Furthermore, we calibrate our model to quantify elasticities and conduct counterfactuals. For this, we rely on estimation techniques of a literature on multi-unit auctions, developed by Guerre et al. (2000), Hortaçsu and McAdams (2010) and Kastl (2011) and extended by Hortaçsu and Kastl (2012), and Allen et al. (2020, 2021).[4]

Outline and conventions. In Section 2 we introduce our model. Here we use prices to express bond values, because it is more intuitive to think through the economics when demand schedules are downward sloping and dealers pay prices to buy for bonds. Starting in Section 3 we take our model to the data. Then we express bond values in yields to maturity as is the case in the data. This makes the value of bonds that have different maturities and coupon payments more comparable. Since yields increase when prices decrease, demand schedules with yields are upward sloping.

Throughout the paper, we refer to markups as the the difference between the price at which the market would clear if it was perfectly competitive and the price at which it clears under imperfect competition; or equivalently, as the difference

[4]Our findings support a contemporaneous paper by Albuquerque et al. (2022). They measure the price elasticity of aggregate demand in Portuguese Treasury auctions and show that it predicts the post-auction return of the same bonds in the secondary market. They suggest that the elasticity may proxy for dealers' risk-bearing capacity.

between the yield at which the market clears under imperfect competition versus perfect competition. In a uniform price auctions, markups increase in price impact–a common object of interest in the finance literature following Kyle (1989).

2 Model

Our innovation is to introduce capital constraints in standard multi-unit auctions (as in Wilson (1979)) to study how the market price and markups change when capital constraints are relaxed. In our benchmark, we model market clearing via a uniform price auction, which may be one-sided, meaning that bidders buy but not sell, or double-sided, so that bidders buy and sell. In practice, many primary markets, for instance in the U.S., clear via uniform price auctions, while trading on an exchange can be approximated via a double-sided uniform price auction (e.g., Kyle (1989)).

There are $N > 2$ dealers who compete in a uniform price auction to buy units of an asset of total supply $A > 0$ for which they pay for in cash (numeraire). Dealer i holds $z_i \in \mathbb{R}$ of inventory of the asset, equity capital $E_i > 0$ and other assets on the balance sheet, which we normalize to 0 w.l.o.g. One unit of the asset pays a return of $R \sim N(\mu, \sigma)$ in the future. In our empirical application, where the asset is a government bond, R represents the return from selling the bond in the secondary market, which is unknown at the time of the auction.

Dealers may be uncertain about the supply A, expected return, μ, of the asset, the inventory positions of other dealers or capital positions. In the simplest version of the model, dealers are uncertain about the supply, thus face aggregate uncertainty, but have no private information or signals about the asset's expected return, their inventory, or capital positions.

Here, we present the simplest version of the model, as it best illustrates the main mechanism at play. Thus, A is drawn from some commonly known continuous distribution on positive support, and all other parameters, including $\mu > 0, z_i \in \mathbb{R}, E_i > 0$, are known among dealers. In our empirical application, supply is random because dealers don't know how much will be issued when they compete. In other settings, the supply might be random due to noise traders. In Appendix A.1 we generalize our

results to the case of private information.

Each dealer submits a continuous and strictly decreasing demand schedule: $a_i(\cdot) : \mathbb{R} \to \mathbb{R}$, which specifies how many units of the asset, $a_i(p)$, the dealer seeks to buy at price, p.

For a given price, the dealer chooses demand to maximize the utility it expects to earn from the wealth, $\omega_i(a_i, p)$, that would be generated if the dealer won amount a_i at price p, subject to a capital constraint:

$$\max_{a_i} \mathbb{E}_R \left[1 - \exp\Big(- \rho_i \omega_i(a_i, p)\Big)\right] \text{ subject to } \kappa_i \leq \frac{E_i}{p(a_i + z_i)}. \tag{1}$$

Paranerer $\rho_i > 0$, measures the dealer's degree of risk-aversion. The future wealth, $\omega_i(a_i, p)$, is equal to the asset payoff, R, net of the prices paid, p:

$$\omega_i(a_i, p) = (a_i + z_i)R - pa_i. \tag{2}$$

The capital constraint is motivated by the Basel III requirement according to which a bank must hold sufficient equity capital, E_i, relative to its total balance sheet exposure. In our case, the total exposure is the nominal amount of the asset the bank holds after the auction, $p(a_i + z_i)$.

Once all dealers have submitted their demand curves, the auction clears at the price, p^*, at which aggregate demand meets total supply, $\sum_i a_i(p^*) = A$, and each bank pays the market clearing price for the amount won, $a_i^* = a_i(p^*)$. After auction clearance, all transactions take place and the asset pays out its return.

We focus on Bayesian Nash equilibrium with linear demand curves (hereafter, equilibrium), which is common in the related literature (e.g., Kyle (1985, 1989), Vayanos (1999); Vives (2011); Malamud and Rostek (2017); Wittwer (2021)). Crucially, this does not imply that dealers can only submit linear demand curves. Instead, it is optimal for dealers to submit linear demand curves when all others do so.

Proposition 1.

(i) In the unique equilibrium dealer i submits demand curve

$$a_i(p) = ((1 + \lambda_i\kappa_i)\Lambda_i + \sigma\rho_i)^{-1}(\mu - (\sigma\rho_i + \Lambda_i\lambda_i\kappa_i)z_i - (1 + \lambda_i\kappa_i)p), \tag{3}$$

with $\Lambda_i = \beta_i \alpha_i \sigma$ *with* $\beta_i = \frac{2}{\alpha_i b - 2 + \sqrt{(\alpha_i b)^2 + 4}}$ *and* $\alpha_i = \frac{\rho_i}{1 + \lambda_i k}$, *where* $b \in \mathbb{R}^+$ *is the unique positive solution to* $1/2 = \sum_i (\alpha_i b + 2 + \sqrt{(\alpha_i b)^2 + 4})^{-1}$, *and* λ_i*'s are pinned down by the system of* N *equations:* $E_i - \kappa_i p^* [a_i(p^*) + z_i] = 0 \forall i$ *where* $p^* : A = \sum_i a_i(p^*)$. *This equilibrium exists for parameter constellations for which* $\lambda_i \geq 0$.

(ii) When dealers are identical ($\rho_i = \rho, z_i = z, E_i = E, \kappa_i = \kappa$), $\lambda_i = \lambda \geq 0 \ \forall i$ *for sufficiently high* κ *and*

$$a_i(p) = \left(\frac{N-2}{N-1} \right) \frac{1}{\rho \sigma} \Big(\mu - \rho \sigma z - (1 + \lambda \kappa) p \Big). \tag{4}$$

To derive an intuition for this equilibrium, consider a dealer who chooses how much to demand at price p. The dealer takes the behavior of the other dealers as given and maximizes its expected utility from winning the asset subject to market clearing and the capital constraint. The optimal demand equalizes the expected marginal utility (LHS) with the marginal payment (RHS):

$$\mu - \rho_i \sigma (z_i + a_i) = (1 + \lambda_i \kappa_i)(p + \Lambda_i a_i) + \lambda_i \kappa_i \Lambda_i z_i \tag{5}$$

The marginal utility is decreasing in the amount of the asset. For the first unit of the asset, the dealer earns the per-unit return, μ. For the next units, the utility becomes smaller, depending on the variance of the asset's return and the dealer's degree of risk aversion.

The marginal payment has several components and depends on the regulatory shadow cost of the capital constraint (the Lagrange multiplier $\lambda_i \geq 0$), and the dealer's price impact, $\Lambda_i \geq 0$. The latter is known as Kyles' lambda, which is 0 when the market is perfectly competitive so that dealers are price-takers. When the constraint is not binding ($\lambda_i = 0$) and dealers are price takers ($\Lambda_i = 0$), the marginal payment is just the price, p, that the dealer has to pay for amount a_i. When the constraint binds ($\lambda_i > 0$) and dealers are price takers ($\Lambda_i = 0$), the marginal payment is the price they have to pay plus a shadow cost that comes from the capital constraint, which similar to an ad-valorem tax: $(1 + \lambda_i \kappa_i) p$. When dealers face a binding capital constraint ($\lambda_i > 0$) and have market power ($\Lambda_i \neq 0$), $\Lambda_i a_i 0$ measures by how much a dealer's

Figure 1: Own and cross demand effect when capital constraints are relaxed

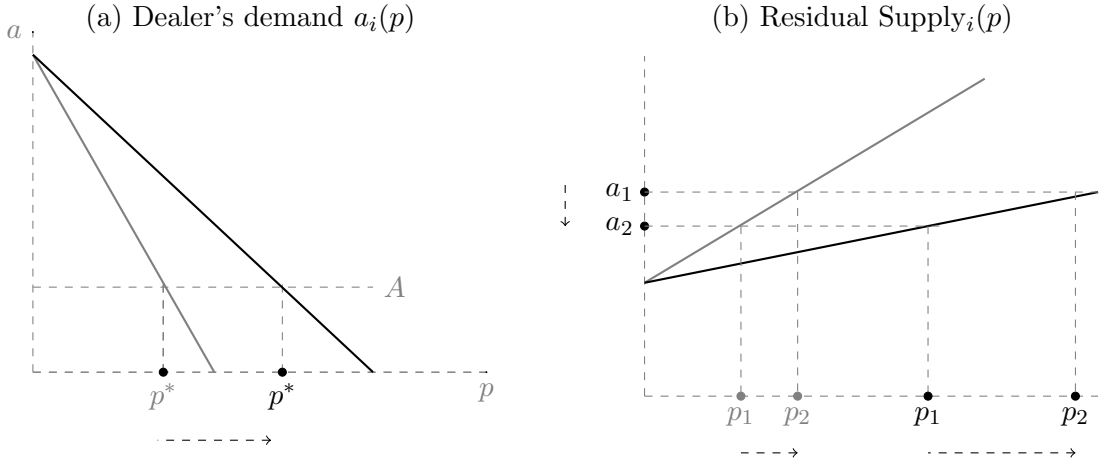


Figure 1 illustrates the change in the dealer's own demand and her residual supply curve when the capital constraints are relaxed in (a) and (b), respectively, for the case in which no dealer carries inventory ($z_i = 0$ for all i). In gray we see the initial demand curve and residual supply curve. Both become flatter, as shown by the black line, when the constraints are relaxed. In (a) we see how this increases the market clearing price, p^*, when supply is fixed. In (b) we see the increase in the price impact, which measures by how much the clearing price changes, $p_2 - p_1$, when the dealer marginally changes her demand from a_1 to a_2.

choice impacts the effective price $(1 + \lambda_i \kappa_i)p$. Importantly, price impact decreases in the shadow costs of capital. For instance, with identical dealers $\Lambda_i = \frac{1}{N-2} \frac{\rho\sigma}{1+\lambda\kappa}$ for all i. Finally, when $z_i \neq 0$, there is an extra term, $\lambda_i k \Lambda_i z_i$ reflects the regulatory cost that comes from the fact that the dealer's existing inventory z_i is evaluated at the market price p in the capital constraint.

The key prediction of the model is about what happens when the capital constraint is relaxed, for instance because the minimal capital thresholds decrease.

Corollary 1. *When capital constraints are relaxed so that λ_i's decrease*

(i) demand $a_i(\cdot)$ becomes flatter, and market price p^* increases

(ii) price impact Λ_i and markups increase for all dealers i.

Figure 1 illustrates two effects from relaxing the capital constraints. The first effect is an own-demand effect. Since the effective price, $(1 + \lambda_i \kappa_i)p$, decreases, it becomes cheaper for the dealer to buy larger amounts. The dealer's demand $a_i(\cdot)$ flattens. The market price increases mechanically, unless supply adjusts.

The second effect comes from the change in demand of the other dealers. This is because the relaxed capital constrained doesn't only affect dealer i, but all other dealers as well. All other dealers submit flatter demand curves, which implies that the residual supply curve that dealer i faces when choosing its demand schedule is flatter. A flatter residual supply curve, in turn, means that the dealer moves the market clearing price more strongly when changing her demand. The dealer's price impact increases.

Take away. Our model helps explain how capital constraints affect asset prices and markups. The main prediction is that both the market price and markups increase when capital constraints are relaxed, which highlights a trade-off for primary market.

In Appendix A.2, we show that this prediction generalizes to discriminatory price auctions, in which winning bidders pay the prices that they offered, not the market clearing price. This auction format is used to sell government debt in many countries, including Canada.

3 Institutional setting and data

To test the predictions of Corollary 1 and to quantify by how much demand, the price (or equivalently the yield) and markups change when capital constraints are relaxed, we use data on Canadian Treasury auctions. It has the attractive feature that dealers submit entire demand functions, which we can link to balance sheet information of each dealer at the company holding level.

Market players. There are eight deposit-taking primary dealers in Canada who are federally regulated.[5] They dominate the Canadian Treasury market and intermediate the vast majority of the daily trade volume with government bonds. More broadly

[5]In total there are eleven primary dealers. One of these dealers is provincially regulated and two are private securities dealers. They face different capital regulation than the eight dealers we study. We therefore do not observe any balance sheet information for these players. Technically, two of the eight banks have multiple dealers. For example, the Bank of Montreal, has two dealers (Bank of Montreal and BMO Nesbitt Burns) who attend different Treasury auctions, and therefore do not compete or share information within an auction. We treat them as one dealer.

speaking, these banks dominate the Canadian banking sector and hold over 90% of the sector's assets.

Primary dealers have a responsibility, as market-makers, to buy bonds from the government and trade them with investors, brokers, or one another to provide liquidity. They hold a substantial amount of bonds on their own balance sheets (see Appendix Figure A1).

Market making is a small part of the bank's total business, which includes accepting deposits, making loans, offering checking or saving accounts and other financial products to individuals and businesses. Therefore, the dealer has no control over most determinants on the bank's balance sheet. A dealer's assets are on average 9% of the bank's total assets (Allen and Usher (2020)). The bank's balance sheet, in turn, is what matters for the regulator since capital requirements must be met at the company holding level.

Treasury auctions. Governments issue bonds in the primary market via regularly held uniform price or discriminatory price auctions. In Canada, auctions are discriminatory price. They take place several days a week. Anyone may participate, but most of the supply is purchased by dealers. The largest eight dealers purchase on average 81% of the supply in order to sell (or lend) on the secondary market.[6] The auction process is described below.

Capital constraints. According to a recent survey among market participants, the Basel III LR represents the most relevant capital constraint when trading government bonds (see CGFS (2016)). This regulatory requirement came into effect in September 2014 to reduce systematic risk—a benefit which we do not consider in this paper. We focus on the cost-side of the constraint, which was empthathized by Duffie (2018) and others.

Formally, the LR measures a bank's Tier 1 capital relative to its total leverage exposure, and must be at least 3%:

[6]This percentage represents how much of the amount that is issued to bidders other than the Bank of Canada, who bids non-competitively, is allocated to the eight largest dealers.

$$\text{LR}_{iq} = \frac{\text{regulatory capital of bank } i \text{ in quarter } q}{\text{total leverage exposure of } i \text{ in } q}.$$

Tier 1 capital consists primarily of common stock and disclosed reserves (or retained earnings), but may also include non-redeemable non-cumulative preferred stock; while the leverage exposure includes the total notional of all cash and repo transactions of all securities, including government bonds, regardless of which securities are used as collateral.[7]

In reality, banks refrain from getting close to the minimal Basel III threshold (see Figure 3b, explained below). One reason for this is that each institution faces an additional supervisory LR threshold. These institutional specific thresholds are communicated to individual institutions on a bilateral basis.[8] They are considered supervisory information and are not permitted to be disclosed to the public. Another reason is that banks tend to hold sufficient conservation buffer for Tier 1 capital so as to avoid punishment in form of restricted distributions (including dividends and share buybacks, discretionary payments and bonus payments to staff).[9]

Data. The unique feature of our data is that we can link how a dealer bids in the Treasury auction to balance sheet information about the dealer's bank.

We obtain bidding data of all regular Treasury auctions between January 1, 2015 and February 1, 2022 from the Bank of Canada. We see who bids (identified by a legal entity identifier) and all winning and losing bids. For consistency, we restrict attention to bids of the eight dealers who are deposit taking for the most part of the

[7]Tier 1 capital consists mostly of common shares and stock surplus, retained earnings, other comprehensive income, qualifying minority interest and regulatory adjustments. The total leverage exposure measures a bank's total assets and several of off-balance sheet items, such as derivatives and repurchase agreements. For more details see: `www.osfi-bsif.gc.ca/Eng/fi-if/rg-ro/gdn-ort/gl-ld/Pages/LR19.aspx#expomea`, accessed on 05/31/2022.

[8]For more details see Section IV. Minimum and authorized leverage requirements at: `www.osfi-bsif.gc.ca/Eng/fi-if/rg-ro/gdn-ort/gl-ld/Pages/LR22.aspx`, accessed on 05/31/2022.

[9]In line with this idea, Barth et al. (2005), Berger et al. (2008) and Brewer et al. (2008) document that bank capital is substantially above the regulatory minimum in countries other than Canada.

paper.

We collect balance sheet information for these eight dealers at the bank level. Specifically, we obtain the LRs and supervisory LR thresholds of each bank. Both are reported quarterly, at the end of January (first quarter), April (second quarter), July (third quarter) and October (fourth quarter of the reporting year) from January 2015 until January 2022 from a data source, called LR.[10] In addition, we obtain the daily aggregated long and short positions in government bonds of the six largest dealer banks from the Collateral and Pledging Report (H4).[11] Finally, we collect information on who holds government bonds—banks versus other investor types—from the National Accounts Canada (Statistics Canada).

In addition, we obtain yields of all trades with Canadian government bonds in the secondary market from November 2015 until December 2020 to better isolate the yield effect of dealer capitalization. These data are collected by the Industry Regulatory Organization of Canada in the Debt Securities Transaction Reporting System (MTRS2.0) since November 2015 and are made available for research with a time lag.

Finally, we collect the Implied Volatility Index for Canadian Treasuries from the Bank of Canada. The index measures the expected volatility of Treasury prices over the next 30 days, similar to the Merrill Lynch Option Volatility Estimate (MOVE) for U.S. Treasuries or CBOE Volatility Index (VIX) for stocks. It is based on option prices on interest rate futures (Chang and Feunou (2014)).

Conventions and summary statistics. Quantities are in million C$, unless stated otherwise. Ratios and yields—which we use from now on instead of prices—are in percent or bps (i.e., $\frac{1}{100}\%$). An overview of the main variables is in Table 1.

[10] One of the banks, HSBC, has a different reporting schedule than the others. Its fiscal year ends in December, instead of October. In our empirical analysis this difference is absorbed when we include dealer fixed effects.

[11] Institutional specific positions must only be reported monthly.

Table 1: Summary statistics

	Mean	Median	Std	Min	Max
Total amount issued (in bn C$)	3.97	3.20	2.33	1	20.6
Average yield (in %)	0.92	0.65	0.63	0.04	2.50
Days to maturity	1,094	352	2,292	99	12,399
Number of dealers per auction	8.00	8.00	0.04	7	8
Number of steps in demand curve	4.74	5	1.67	1	7
Maximal amount demanded (in mil C$)	741	600	569	0.48	8,240
Amount dealer won (in mil C$)	277	150	395	0	5,739
Quarterly LR (in %)	4.41	4.36	0.28	-	-
Implied Volatility Index (in %)	0.46	0.25	0.77	0.04	7.57

Table 1 shows the average, median, standard deviation, minimum and maximum of key variables in our sample. Our auction data goes from January 1, 2015 until February 1, 2022 and counts 917 auctions. In total there are 21 different securities. The min and max LR are empty because we cannot disclose this information.

4 Evidence in favor of our model

We now provide supporting evidence of our model. Afterwards, we calibrate our model to quantify by how much yields and markups change when capital constraints are relaxed.

4.1 Demand effect

To provide evinces that demand becomes flatter when the capital constraint is relaxed, we leverage two features. First, government bonds, central bank reserves, and sovereign-issued securities that qualify as High Quality Liquid Assets (HQLA) were temporarily exempted from the LR constraint starting on April 9, 2020, to buffer the negative effects of the liquidity crisis triggered by the COVID-19 pandemic (see Figure 3b).[12] The exemption of government bonds and HQLA ended on December

[12]The announcement to start the exemption period is available at: `www.osfi-bsif.gc.ca/Eng/fi-if/in-ai/Pages/20200409-dti-let.aspx`, accessed on 05/31/2022. The announcement to end it is here: `www.osfi-bsif.gc.ca/Eng/fi-if/in-ai/Pages/lrfbunwd.`

31, 2021, while reserves continued to be excluded.[13] Second, in absence of the exemption some banks in my data faced higher, i.e., stricter, capital thresholds than other banks. According to our model, the demand of these banks should have become flatter during the exemption period than the demand of other banks

To show this, we construct a measure of the slope of the demand and analyze how slopes of banks with higher institution-specific capital thresholds changed relative to those of the other banks.

Slope measures. Creating a slope measure is challenging because it must be dealer and auction-specific so as to account for differences in capitalization, capital requirements and market conditions. For instance, we cannot simply regress demand on prices or yields and use the regression coefficient as our slope measure. Not only are prices endogenous, but this approach would eliminate the variation across time and dealers that we need.

To construct a slope measure, assume for a moment that in the auction dealers can submit linear demand curves that map from prices to quantities, like in the model. Dealer i's demand on day t for security s would be: $a_{its}(p) = intercept_{its} - slope_{its}p$. If this was so, we could read the intercept and slope off the data. The intercept would be the amount that the dealer demands at a zero price, and the slope would be the ratio between this amount and the intercept of the demand curve with the price-axis.

In reality, there are two differences. The first is that dealers cannot submit linear demand curves but have to submit step functions with maximally 7 steps. A dealer i submits $K_{its} \leq 7$ quantity-price tuples: $\{a_{itsk}, p_{itsk}\}_{k=1}^{K_{its}}$. This implies that the measure we introduce,

$$slope_{its} = \frac{\max_k\{a_{itsk}\}}{\max_k\{p_{itsk}\}} \text{ for } K_{its} > 1, \tag{6}$$

is an approximation (see Figure 2). The second difference is that the value of the bond is expressed in yields rather than prices, which means that the submitted demand

aspx, accessed on 05/31/2022.

[13] In Canada, quantitative easing is conducted by the central bank buying government bonds from banks with settlement balances, i.e., reserves.

curves are upward sloping. To incorporate this, we convert the maximal price in equation (6) into the corresponding yield.

One concern with slope measure (6) is that it relies on two extreme points on the demand curve. Ex ante, the dealer does not know where the market will clear, and submits bids at prices that may win with positive probability. However, ex post with finite data, it may be that we don't observe dealers ever winning at extreme points on their demand curves.

To ensure that our estimation results are not biased by extreme points, we conduct robustness checks with three alternative measures.[14] Among all slope measures, measure (6) is our preferred one. It is intuitive and can be computed for essentially all demand curves for each dealer and auction. The measure can account for differences in capitalization, capital requirements and market conditions over time and across all dealers. In contrast, our alternative slope measures rely on a more restricted sample of bids.[15]

Event study. Given that capital requirements must hold on a quarterly basis, we collapse the data on that level. We regress the average slope in the demand function of dealer i in quarter q for security s on indicator variable that assume value 1 k quarters before/after the first event quarter (2020q2), D_k, multiplied by the bank's $threshold_{ik}$ supervisory LR threshold in that quarter. We include quarter-security fixed effects, ζ_{qs}, to absorb common unobservables that affected dealer demand, such as the start of QE or COVID-related demand and supply factors.

$$slope_{iqs} = \alpha + \sum_{k=-K}^{K} \gamma_k * D_k * theshold_{ik} + \zeta_{qs} + \epsilon_{iqs}, \tag{7}$$

[14]One other way to construct a slope measure in other settings, would be to fit straight line through each submitted demand curve. In our setting, in which the median (maximal) number of steps in a demand curve is four (seven), this would mean running OLS regressions through only a few data points.

[15]This is especially true when measuring the slope of demand locally, around the market clearing price. This local measure only considers 69% of all demand curves—those of bidders who win at auction. This is problematic, for instance, if dealer capitalization affects how aggressive the dealer bids, which is what our model predicts.

Figure 2: Example of a demand function with 6 steps

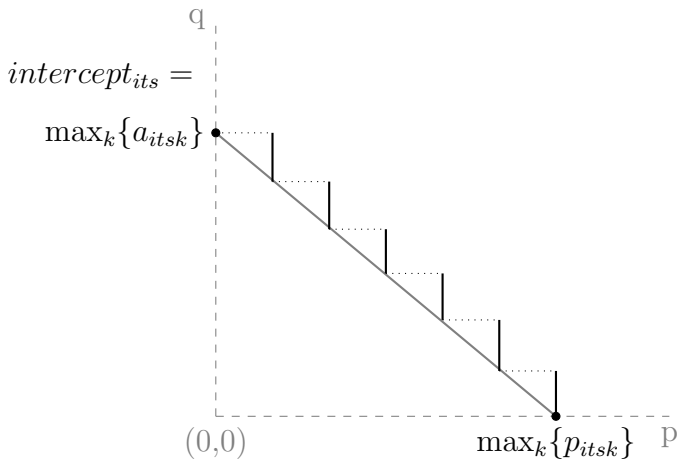


Figure 2 illustrates how we measure the slope of demand of dealer i on day t for security s. In black, we show an example of a step-function, $\{a_{itsk}, p_{itsk}\}_{k=1}^{6}$, that a bidder could submit at auction (with prices instead of yields). In gray, we show a continuous, linear demand function, $q(\cdot)$, as in Proposition 1, which connects the maximal amount that the bidder asks for, $\max_k\{a_{itsk}\}$, with the maximal price that it is willing to pay, $\max_k\{p_{itsk}\}$. We use the the slope of this auxiliary function to approximate the "slope" of the step function, and convert prices into yields.

The slope is measured in million C$ per 1 bps. For, instance, a slope of 1 means that a dealer demands C$ 1 million less when the yield increases by 1 bps. The threshold is also expressed in bps.

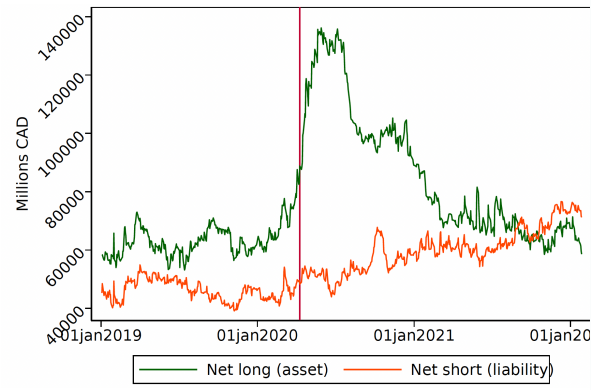
The parameter of interest, γ_0, tells us by how much the slope of a bank that faces a tighter constraint (higher supervisory LR threshold) changes relative to the slope of a bank that faces a less stringent constraint (lower supervisory LR threshold), when government bonds were exempt, and similarly for γ_7.

We find that the estimated coefficients are not statistically different from 0 before the policy change, which means that banks with different capital thresholds submitted demand curves with similar slopes (see Figure 4). During the exemption period, the slope of banks with higher capital thresholds were significantly lower than those of banks with lower thresholds. It jumps back when the exemption ended. Both is in line with our model.

The size of the effect is large (C$1 million per bps). It suggests that, during the exemption period, a bank whose capital threshold is 1 bps above the threshold of

Figure 3: The effect of the exemption on Treasury positions and the LR

(a) Aggregated positions in Treasuries



(b) Time series of LR for an average bank

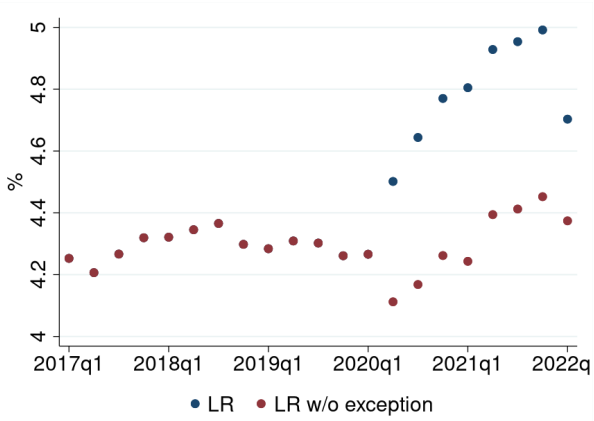


Figure 3a shows the aggregated amount of Canadian government bonds that the biggest six Canadian banks hold in long (in green) and short (in red) positions in millions of C$ from January 2019 until February 2022. The vertical line is April 9, 2020, when government bonds were exempt from LR. Figure 3b shows the time series of the LR (in %) of an average bank. In blue, we show the actual LR. In red the counterfactual LR that the average bank would have had if central bank reserves and sovereign-issued securities that qualify as high quality liquid assets and exposures related to the US Government Payment Protection Program (PPP) were not exempt. In 2022q1, the LR does not get back to its original level, partially because central bank reserves are still exempted.

Figure 4: Change in the slope

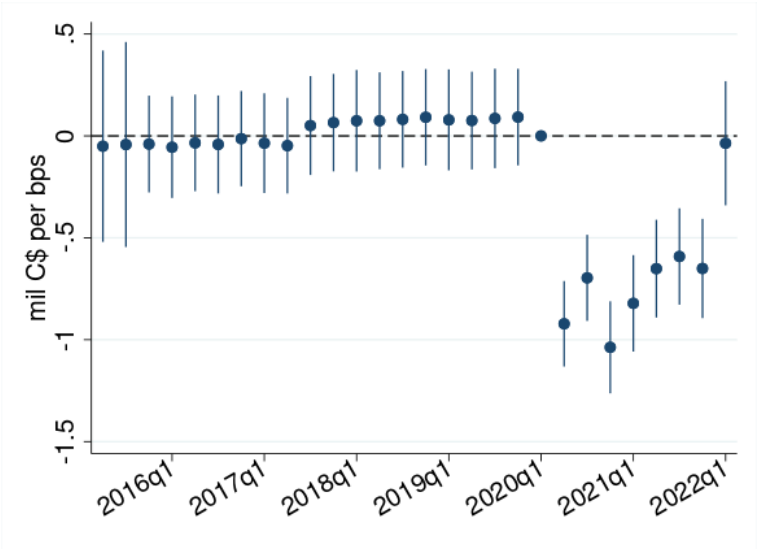


Figure 4 shows the γ_k estimates and 95% confidence intervals of the regression (7): $slope_{iqs} = \alpha + \sum_{k=-K}^{K} \gamma_k * D_k * threshold_{ik} + \zeta_{qs} + \epsilon_{iqs}$. All magnitudes are relative to the benchmark in 2020q1. The slopes are in million C$/bps, thresholds are in bps.

another bank reduces its demand by C$ 1 million less than the other bank in response to a 1 bps yield increase. This change is sizable compared to the average amount a dealer wins at auction (C$ 277 million).

Interpretation. The estimated relationship would be causal under two conditions. First, capital thresholds were not changed in response to, or set in expectation of the temporary exemption. This is plausible given that COVID was not predictable when most of the capital thresholds were last adjusted. Second, the exemption was an exogenous event. This means that the Canadian regulator did not choose to change the LR requirement in response to how dealers bid in the primary auctions, which seems is unlikely given that Canada was part of a global response (see Bank of International Settlement (2020)). This also means that there were no systematic changes over time that affected the slope of different dealers differently, other than the change in LR.

Two confounding factors come to mind. First, the Bank of Canada increased the maximal bidding limits from April 2020 until June 2021. This was to allow dealers to buy larger amounts of government bonds, even though pre-COVID maximal bidding limits were typically not binding (see Appendix Figure A5). Second, the Bank of Canada started buying government bonds in the secondary market via quantitative easing from April 2020 until October 2021. Both of these policy interventions were meant to help ensure that dealers continued to buy sufficiently in the primary market.[16] Thus, if anything, these interventions likely increased the amount a dealer asked for at auction. By definition, such increases would have increased the slope measure (6). We find the opposite and therefore don't think that the change in bidding limits or quantitative easing drives the drop in 2020q2. Moreover, neither of the two confounding factors were present in 2022q1, when the slop jumps back up.

[16]This raises the concern that dealers were at the minimal bidding limits. The minimal limits are only soft constraints since dealers are given six months to improve its performance if it falls below the minimum. They are bank-specific and the exact numbers are unknown to us. We know that for most banks the minimal limit is around 10% and do not see that banks are more likely to be at that limit during 2020–2021 (see Appendix Figure A5).

Robustness analysis. We conduct a series of robustness checks. First, we estimate regression (7) with leverage ratios LR_{iq} instead of capital thresholds to exploit variation in these ratios (see Appendix Figure A2). The estimates are qualitative similar, but the change in the slope is less sharp when the exemption period ends. One reason for this is that dealers who were most positively impacted by the LR exemptions demanded larger amounts in 2020q2 than in subsequent quarters (see Appendix Figure A4). This mechanically increases the slope measure after the first exemption quarter.

Second, in Appendix Figures A3, we add dealer fixed effects to take out time-invariant unobservable dealer characteristics, but warn that this regression could be over-specified when using the capital thresholds given that they don't change often.

Third, we use the alternative slope measures, described above, to show that the change in the slope is not driven by the way we construct our slope measure (recall Appendix Figures A7). By definition, the size of the slope effect depends on how we compute the slope measure. Importantly, the qualitative finding is robust across all specifications.

Fourth, we exclude dealers who hit the pre-COVID bidding limits more frequently than 0.25% to show that the main results are not driven by dealers who go over these limits (recall Appendix Figure A6).

4.2 Yield effect

When demand becomes flatter the market clearing yield must decrease, all else equal. This is a mechanical effect in theory, which is hard to show in the data. The reason is that we only observe one market clearing yield for each auction. We don't see the counterfactual scenario in which demand curves would have been flatter and the market would have cleared at a different yield. We can no longer rely on variation of capital or leverage ratios or thresholds across dealers. However, we can compare market yields across time, and control for unobservable factors that moved yields but were unrelated to dealer capitalization.

To test whether the yield decreases as the leverage ratio increases—either because the bank already holds sufficient capital which lowers the shadow cost of the capital

Table 2: Correlation between yield and LR

	(OLS)	(FE1)	(FE2)
LR	-0.360^{***}	-0.370^{**}	-0.245^{**}
	(0.0362)	(0.0411)	(0.0521)
controls	–	–	✓
fixed effects	–	✓	✓
Observations	2912	2912	2904
Adjusted R^2	0.032	0.679	0.789

Column of Table 2 shows results of $yield_d = \alpha + \beta LR_{qi} + \epsilon_{ti}$. In (FE1) we add the dealer and year fixed effect. In (FE2) the control variables. Yield and LR are in %. Standard errors are in parentheses, clustered at the dealer level in (FE1) and (FE2). * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

constraint, or because capital requirements are relaxed—we regress the average auction clearing yield on day t on the quarterly leverage ratio of a dealer, LR_{qi}, and two control variables, as well as dealer-fixed effects (ζ_i) and year fixed effects (ζ_y):

$$yield_t = \alpha + \beta LR_{qi} + controls_t + \zeta_y + \zeta_i + \epsilon_{ti}.$$

First, to take out unobservable factors that move yields, such as interest rate uncertainty and inflation risk, we control for the yield at which the closest substitute to the issued bond is traded on that day in the secondary market, $benchmark_yield_t$.[17] We define the closest substitute as the bond with the closest maturity date to the one issued, on average the maturity differs by few days. Second, to remove any effect extra supply might have on the yield, we control for the supply of the auction, $supply_t$.

In line with the model's prediction, we find a negative relationship between the auction yield and the leverage ratio (see Table 2). To get a sense of the size of the effect, recall that the leverage ratio increased from an average of 4.3% to 4.5% (recall Figure 3b). These coefficients say that this decreased the auction yield by 5–7 bps, which is a significant drop given the low yields in the sample.

[17]One concern is that the closest substitutes are less liquid than the bonds issued due to an on-the-run effect. This effect is less common in Canada because most bonds are re-issued multiple times to avoid low liquidity of a particular security.

The OLS estimate would be downward biased (and hence larger in absolute value than it should be) if LR is positively correlated with the error term. This would be the case if there were unobservable factors that lead banks to decrease the LR and decrease the yield. Before April 9, 2020, one way for this to happen is if banks actively increased their LR in response to some negative capital shock by buying less government bonds in a way that decreases the total asset exposure but keeps capital constant. Then, since dealer demand is downward (upward) sloping in price (yield), the market yield would decrease.

Take away. Our empirical evidence provides support for our model hypothesis—dealer demand becomes flatter when their institutions weaker capital constraints. This decreases the market yield. To quantify these effects and avoid endogeneity issues, we take our model to the data.

5 Quantification

Our goal is to quantify by how much the yield and markups changes when capital constraints are relaxed. Both effects depend on the shadow cost of the capital constraint, $\lambda\kappa$, and the dealer's risk aversion, ρ, in addition to observables, such as market volatility.

5.1 How to identify risk aversion and shadow costs?

To estimate these parameters, we face three main challenges that stem from the fact that Treasury auctions are more complicated in reality than we can capture with a tractable theory. First, the auction is discriminatory price, not uniform price. Second, demand functions are step-functions as in Kastl (2011). Both complicates the analysis. Third, dealers are not the only bidders who bid in the auction. Customers participate via dealers, which means that dealers might obtain information from observing their customer bids.

Main idea. To overcome these challenges, we use insights and techniques from the empirical literature on auctions (Guerre et al. (2000): Hortaçsu and McAdams

(2010); Kastl (2011); Hortaçsu and Kastl (2012); Allen et al. (2022)). For this, we adopt Hortaçsu and Kastl (2012)'s empirical auction model that incorporates the key institutional features of Canadian Treasury auctions.

The main idea is that we can back out how much bidders are truly willing to pay from the bids they submit under the assumption that bidders are rational and play an equilibrium of the auction game. With the bidders' estimated willingness to pay—which depends on the shadow cost of the capital constraint and the dealer's risk aversion—we can separately identify these parameters by leveraging the fact that Treasuries were exempt from the constraint. To do this, we do not have to solve for an equilibrium in closed form. It suffices characterize optimality conditions of an equilibrium, which implies that we can work with a less stylized model that closely fits the actual auction.

Identifying assumptions. To remain concise and focus on our contribution, we only discuss the main identifying assumptions that we impose in our paper. We refer to Hortaçsu and Kastl (2012) for details.

There are N_D potential dealers and N_C potential customers who participate in auction t. Each dealer and customer draws private information ξ_{ti} about her true willingness, $v_{ti}(q)$, to pay for amount q. ξ_{ti} is drawn independently from all other bidders according to atomless distributional functions $F_t^D(\xi_{ti})$ and $F_t^C(\xi_{ti})$ for dealers and customers, respectively.

Ex-ante, before drawing private information, all dealers are identical, and so are customers, but across these two bidder groups, bidders may be asymmetric. This implies that all dealers share the same degree of risk aversion, ρ_t and the same shadow cost of capital $\lambda_t \kappa_t$ within the same auction.

To determine how much a bidder is wiling to pay in auction t, we rely on our theory. In particular, equation (8) characterizes how much a dealer is truly willing to pay, which is equivalent to the price a bidder would submit if she was a price-taker (i.e., $\Lambda_i = 0$). Adjusting the notation to highlight that parameters may change across

auctions t and account for the fact that dealers are ex-ante identical, we rearrange

$$\mu_t - \rho_t \sigma_t (z_{ti} + a) = (1 + \lambda_t \kappa_t)(v_{ti} + \Lambda_{ti} a) + \lambda_t \kappa_t \Lambda_{ti} z_{ti} \tag{5}$$

with $\Lambda_{ti} = 0$ to obtain the dealer's true willingness to pay for amount a:

$$v_{ti}(a) = \xi_{ti} - \left(\frac{\rho_t \sigma_t}{1 + \lambda_t \kappa_t} \right) a. \tag{8}$$

According to our theory, $\xi_{ti} = (\mu_t - \rho_t \sigma_t z_{ti})(1 + \lambda_t \kappa_t)^{-1}$, but for our estimation, we don't have to impose any specific functional form on ξ_{ti}.

Finally, to identify dealer's risk aversion and the shadow cost of the capital constraint, we assume that the dealer's risk aversion did not change in auctions close to the policy change, $\rho_t = \rho_q$, and that the cost is constant within a quarter, $\lambda_t \kappa_t = \lambda_q \kappa_q$. Here, we include all auctions in the quarter before and after the two policy changes motivated by the fact that capital requirements are reported quarterly.

Estimation procedure Our estimation procedure has two steps.

First, we estimate the dealers' true willingness to pay, $\hat{v}_{tik} = \hat{v}_{ti}(q)$, for each submitted amount q, or, equivalently submitted step k, from the necessary equilibrium conditions (characterized in Hortaçsu and Kastl (2012), Proposition 1). These conditions depend on the distribution of the market clearing price. To estimate this distribution for each bidder and auction, we adopt the resampling method of Allen et al. (2022) who generalize Hortaçsu and Kastl (2012)'s method.

The core idea is to fix a bidder and draw from the submitted bids of all other dealers to simulate one possible market outcome. Repeating this many times, gives the distribution of the market clearing price for each bidder. The resampling becomes more complicated when accounting for the fact that there are two bidder groups and that dealers can observe their customer's bid, but the main idea remains the same. We refer to Allen et al. (2022) or Hortaçsu and Kastl (2012) for details of the resampling procedure.

Second, we leverage the assumption that a dealer's willingness to pay is linear and that its slope is independent of the dealer's private information (recall equation (8)).

This together with the fact that most dealers submit a step function with more than two steps, allows us to estimate a slope coefficient, β_t, from regressing the dealer's estimated value at step k, $\hat{v}_{tik}$, on the amount she demanded at that step a_{tik} and a bidder-time-auction fixed effects, ξ_{ti},

$$\hat{v}_{tik} = \xi_{ti} - \beta_t a_{tik} + \epsilon_{tik}, \tag{9}$$

using values from dealers who submit more than two steps in auction t.

We normalize each slope coefficients $\hat{\beta}_t$ by the Implied Volatility Index for Canadian Treasuries, shown in Figure 5a, which measures σ_t in the dealer's willingness to pay (8). During the exemption period—in which the shadow cost of the capital constraint are 0—the normalized slope coefficient, $\frac{\beta_t}{\sigma_t}$, equals the dealer's risk aversion ρ_t. Outside of this period, $\frac{\beta_t}{\sigma_t} = \frac{\rho_t}{1+\lambda_t\kappa_t}$.

Finally, under the assumption that risk aversion does not change around the policy change and that the shadow cost of capital is constant within a quarter, we compare the slope coefficient before and after the policy change to back out our parameters of interest. Alternatively, we can estimate these parameters in one step running the following regression

$$\hat{v}_{tik} = \zeta_{ti} + \rho \times exempt_t \sigma_t a_{tik} + \frac{\rho}{1+\lambda\kappa} \times (1 - exempt_t)\sigma_t a_{tik} + \epsilon_{tik} \tag{10}$$

using estimated values, $\hat{v}_{tik}$, and respective quantities a_{tik} of dealers who submit more than one step in an auction t during 2020q1 and 2020q2 when the exemption period started. For the end of the exemption period, we use data from 2021q4 and 2022q2. Indicator variable $exempt_t$ is 1 in 2020q1 and 2022q1, respectively, and 0 otherwise, σ_t is the daily Implied Volatility Index and ζ_{ti} is a dealer-auction-time fixed effect.

5.2 Estimated parameters and elasticities

Risk aversion and shadow costs. The distributions of $\frac{\beta_t}{\sigma_t}$ during and outside of the exemption period, shown in Figure 5b, tell us that ρ_t is small with a median of around 0.001. This is reassuring since we would expect global banks to be able to diversity away most of their risk by managing their portfolio. In addition we see that

Figure 5: Implied Volatility Index and normalized coefficients of regression (9)

(a) Implied Volatility Index: σ_t (b) Normalized coefficients: $\frac{\hat{\beta}_t}{\sigma_t}$

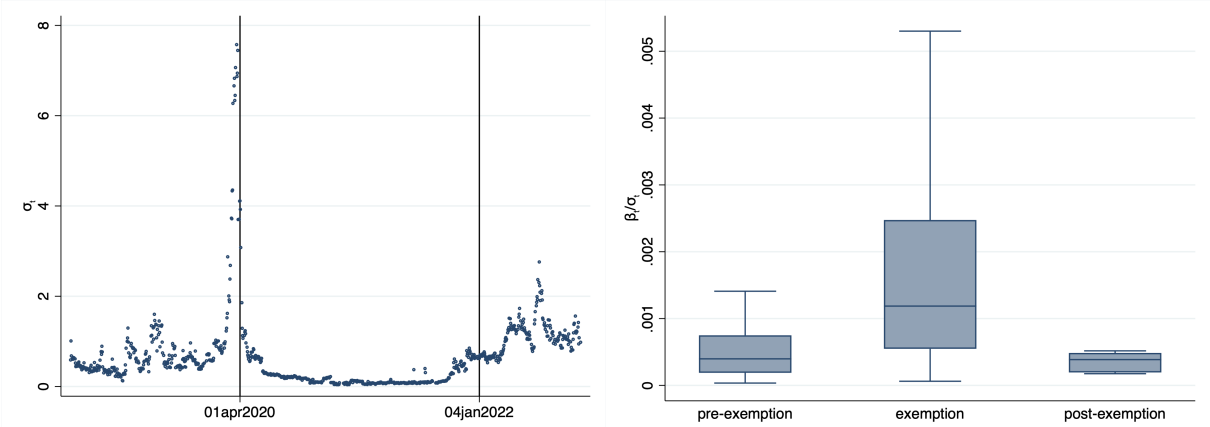


Figure 5a displays the time series of the daily Implied Volatility Index (in %) of the Canadian Treasury market from 2019 until March 2022. Figure 5b shows the distribution of the estimated slopes coefficient of the dealers' willingness to pay in auction t, $\hat{\beta}_t$ of regression (9) with dealer values in % and quantities are in million C$, normalized by the Implied Volatility Index (in %), σ_t, for three time periods: before the exemption of Treasuries from the LR (2019q1–2020q1), during the exemption period (2020q1–2021q4) and after the exemption (2022q1).

ρ_t varies across auctions during the exemption period. One reason for this is that different auctions offer government bonds of different maturities and risk aversion varies in the length to maturity. Longer bonds are more risky to buy than short T-bills (see Appendix C for details). Finally, the median $\frac{\beta_t}{\sigma_t}$ outside of the exemption period is lower than the median during the exemption period, which suggests that the shadow cost of capital are strictly positive in 2020q1 and 2022q2.

In line with these insights, we estimate low risk aversion and high shadow costs using regression (10): see Table 3. The risk aversion is +0.0001 for 2020q1-2020q2 and +0.0003 for 2021q4-2022q1. This means that a dealer's average willingness to pay decreases by only C$2.77 when going from winning nothing to winning the average amount (C$277 million). The dealer appears close to risk neutral, which would be the case if the willingness to pay was perfectly flat.[18] The shadow cost of capital is

[18]Banks became slightly more risk averse in 2021q4-2022q1 relative to 2020q1-2020q2. One reason for this is that dealers are uncertain about when the exemption for reserves and settlement balances will be lifted. This would tighten their LR. In addition, they might be concerned that the Bank of Canada will have to start unwinding all the bond QE-purchases.

high with 0.96 in 2020q1-2020q2 when investors wanted to sell Treasuries and dealers were asked to absorb large amounts onto their balance sheet, tightening constraint. The cost decreases to 0.30 in 2021q1-2022q4 when the Treasury market had calmed down.

As a sanity check, we also estimate regression (10) with submitted, observed bids, instead of estimated values. We expect to find parameters which are similar in magnitudes but not identical, because dealers shade their bids.[19] The estimates in Table 3 confirm this conjecture. Both, risk aversion and shadow costs are similar in size to those before. Both are slightly biased downward. The reason is that dealers shade early steps, i.e., small amounts, more strongly than higher steps, i.e., large amounts (see Figure 6). This implies that the dealer's true willingness to pay is steeper than the submitted bidding function.

The high shadow cost of capital suggests that it is not profitable for dealers to buy Treasuries in the primary market. To see this, consider a dealer 2020q1-2020q2 who holds no inventory position going into the auction. To buy a of bonds, a dealer must pay weakly more than p^*a in a discriminatory price auction plus $0.96p^*a$ due to the capital constraint. In return, the dealer earns Ra from selling the bonds in the secondary market. For this transaction to be profitable it must be that the dealer can sell the bond at a price that is at least double the auction price in the secondary market. This never happens in the data.

This raises the question why any dealer would want to participate in Treasury auctions—addressed in a companion paper (see Allen et al. (2022)). Broadly speaking this suggests that it must be valuable for banks to have the primary dealer status, otherwise we should observe more banks existing the market. Given that primary dealers are carefully chosen by the government and regulated more heavily, the status

As primary dealers, the banks have an obligation to buy these bonds, which can increase their exposure and lower the LR.

[19] In line with the literature, shading is a couple of basis points (e.g., Chapman et al. (2007); Kang and Puller (2008); Kastl (2011); Hortaçsu et al. (2018); Allen et al. (2020, 2022)). These factors are small in absolute terms but sizable compared to the low market clearing yields on the four auction days: 44.7 bps, 43.6 bps, 47.9 bps and 56.2 bps on April 8 2020, April 14 2020, December 21 2021, and January 05 2022, respectively.

Table 3: Estimated risk aversion and shadow cost parameters from regression (10)

(b) With values as independent variable

	2020q1-2020q2		2021q4-2022q1	
ρ	$+1.52/10^{4***}$	$(0.033/10^4)$	$+3.96/10^{4***}$	$(0.155/10^4)$
$\lambda\kappa$	$+0.965^{***}$	(0.168)	$+0.302^{**}$	(0.115)
N	23,074		12,894	

(b) With bids as independent variable

	2020q1-2020q2		2021q4-2022q1	
ρ	$+0.686/10^{4***}$	$(0.010/10^4)$	$+2.050/10^{4***}$	$(0.046/10^4)$
$\lambda\kappa$	$+0.844^{***}$	(0.169)	$+0.169^{*}$	(0.076)
N	23,074		12,894	

Tables 3(a) shows the estimate of $\hat{v}_{tik} = \zeta_{ti} + \rho \times exempt_t \sigma_t q_{tik} + \frac{\rho}{1+\lambda\kappa} \times (1 - exempt_t)\sigma_t q_{tik} + \epsilon_{tik}$ with values expressed as yields to maturity in %, and quantities are in million C$. In (b) we replace the estimated values by the observed bids b_{tik}. Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

signals trustwothyness and stability. This helps to attract bank clients who seek to invest outside of the government bond market. When the benefit of having the primary dealer status no longer out-weights the cost, dealer exist the market. This has happened several times since the first Canadian Treasury auction took place.

Elasticities. With the estimated risk aversion parameter and shadow costs, we can approximate by how much the market price and market power changes when the capital constraint is relaxed. For this, we leverage the following statement.

Corollary 2. *When the shadow cost of capital increases by 1%, the market price and market power—defined as the difference between the price that would arise if dealers were price takers and the price that actually arises—increase each by*

$$\eta = \frac{1}{1 + \lambda\kappa} - 1\%. \tag{11}$$

When values and bids are expressed in yields rather than prices, the market yield decreases but market power increases by η%.

Figure 6: Distribution of bid shading per step k

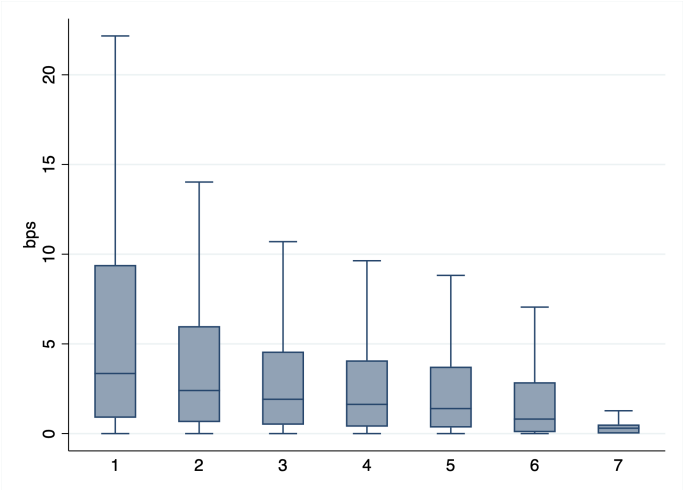


Figure 6 shows box plots of how much dealers shade their bids at each of the seven steps. Formally it is the difference between the submitted yield bid and the estimated value, both in bps. The distribution for each step is taken over dealers and auctions.

This holds in uniform and discriminatory price auctions with ex-ante identical dealers who submit linear demand schedules (see Appendix A for details). In practice, demand schedules are step-functions. However, they are approximately linear, in that the R^2 of regression (9) with bids instead of values is high (see Appendix Table 4). Therefore, we can approximate the effect on the market price and market power with equation (11).

The point estimates of the shadow costs of Table 3 imply an η of 0.49% and 0.23% in 2020q1-2020q2 and 2021q4-2022q1, respectively. This means that the market yield increases by 0.23%–0.49% if the shadow cost increases by 1%. For instance, the average yield of 193 bps would increase by 0.23%–0.49% * 193 bps = 0.4-0.9 bps.

In comparison, the reduced-form evidence says that a one percentage point increase of the LR—which moves the bank further away from the minimal capital threshold and thus decreases shadow costs—increases the yield by roughly 25–36 bps. This means that a 23% increase of the average LR (prior to the exemption=4.2%) increases the average yield by 25/193–36/193=12%–18%. Thus, a 1% increase in the average LR increases the yield by roughly 12/23%–18/23% = 0.57%–0.78%. These numbers are similar to our calibrated yield effect. This provides a validation for our

model since we haven't used this information to estimate it. Further, the fact that the elasticities implied by the regression analysis are larger than the calibrated elasticities is in line with our conjecture, described above, that the regression coefficients might be biased upward in absolute value because of endogeneity.

Counterfactual. With the model we can quantify by how much the auction yield and market power would have changed had the regulator not changed the LR requirement. For illustration, consider 1Y-bond auctions around both policy changes. The first auction after the LR was relaxed (on April 14, 2020) cleared at a yield of 51 bps. The average amount by which a dealer shaded her bid at market clearing, which approximates the markup due to market power, was 2.12 bps. Had the LR not been relaxed—which implies a 100% increase in the shadow cost of the capital constraint—the auction would have cleared at a yield of 75 bps with a markup of 1.14 bps. The first auction after the LR was tightened (on January 5, 2022) cleared at 89 bps, with average shading of 1.79 bps at market clearing. Had LR not been relaxed, the auction would have cleared at 47 bps with yield markup of 2.63 bps.

This highlights a new trade-off that regulators should take into account (in addition to the way the LR affects trading in the secondary market and concerns about systematic risk) when deciding whether to relax or tighten capital constraints. Relaxing capital constraints decreases yields but increases market power. Whether the effect is sizable in absolute terms depends on the interest rate level. If rates and with that yields are low—as is the case in our sample—the absolute effect is small. However, with raising interests rates and growing balance sheets of banks, the trade-off may become first order in the future.

6 Conclusion

This paper studies if and how the capitalization of dealers affects asset demand and, with that, prices, when dealers have market power. We introduce a model to to show that weaker capital requirements lead dealers to demand more of the asset at higher and more manipulated prices. We test the model's prediction and calibrate the model with data on Canadian Treasury auctions, where we can link asset demand

to balance sheet information of individual intermediaries. Our findings highlight that weaker capital requirements reduce the funding cost of debt but increase market power.

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Appendix

A Model extension: Private information

Here we extend our model to incorporate private information. In line with the empirical section of the paper, we let dealers be ex-ante identical and private information be independent. All proofs are in Appendix B.

A.1 Uniform price auction

In our benchmark model, potentially asymmetric dealers face aggregate uncertainty. In the empirical model, dealers are ex-ante identical and have private information. Here we show that the model's prediction generalize to such a setting. In reality,

dealers could be uncertainty about the asset's mean return, their inventory or equity positions. We focus on private information about inventory positions. The other cases are analogous.

There are two main differences compared to the benchmark model. First, dealers are ex-ante identical ($E_i = E, \kappa_i = \kappa, \rho_i = \rho \ \forall i$); each draws an inventory position z_i independently from all other dealers from some distribution. She observes the position privately prior to the auction. In addition, all dealers observe the aggregate inventory positions, $\sum_i z_i$. Second, we let dealers balance out their total exposure after the auction with one another or in an outside market. This assumption reflects the fact that banks try to achieve a balanced exposure by the end of the quarter. Further, it makes the model tractable because it ensures that dealers can predict the Lagrange multipliers, λ_i, of their competitors.

We model the balancing process in reduced form by assuming for each z_i and market price p there is a $x_i(p)$ such that $a_i(p)+z_i+x_i(p) = \eta(p)$, where $a_i(\cdot)$ is the dealer's demand schedule, and $\eta(\cdot)$ is a mapping from the price to the total exposure a dealer carries when the capital constraint must be satisfied. In reality this happens at the end of each quarter. To achieve tractability within the linear-demand environment, we assume that $\eta(p)$ is linear, i.e., $\eta(p) = \alpha - \beta p$ for some $\alpha \in \mathbb{R}^+, \beta > 0$. Exposure decreases in price as you might think of it as demand curve.

Summarizing, the sequence of events is as follows:

1. Each dealer observes her inventory position, z_i, drawn iid from some distribution, in addition to the aggregate inventory, $\sum_i z_i$.

2. Each dealer submits her demand schedule, $a_i(\cdot)$.

3. The auction clears at price $p^* : \sum_i a_i(p^*) = A$, and dealers balance out their total exposure, so that this exposure equals $\eta(p^*)$. The asset pays its return and all transactions are made.

We show that there is an equilibrium that has a similar shape to the one in the benchmark model.

Proposition 2. *There exists an equilibrium in which dealer i submits*

$$a_i(p) = (\Lambda + \sigma\rho)^{-1}\Big(\mu + \alpha\kappa\Lambda\lambda - \sigma\rho z_i - (1 + 2\beta\kappa\Lambda\lambda)p\Big)$$

with $\Lambda = \frac{-(N-2)+\sqrt{(N-2)^2+8\beta\kappa\lambda(N-1)\rho\sigma}}{\sqrt{4\beta\kappa\lambda(N-1)}}$ *and* λ *is such that* $E - \kappa p^*\eta(p^*) = 0$ *where* p^* : $\sum_i a_i(p^*) = A$ *as long as* $\lambda \geq 0$*, which is the case when* κ *is sufficiently low given all other parameters.*

Like in the benchmark model, each dealer chooses how much to demand at each price p so as to equate the marginal utility and marginal payment:

$$\mu - \rho\sigma(z_i + a_i) = p + \Lambda_i a_i + \Lambda_i\lambda_i\kappa\left[\eta(p) + p\frac{\partial\eta(p)}{\partial p}\right] \tag{12}$$

The marginal payment is slightly different from before because the dealer now anticipates that she holds $\eta(p)$ of total exposure on her balance sheet at the end of the game. The constraint now binds when $E = \kappa p\eta(p)$ rather than when $E = \kappa p(a_i + z_i)$. The rest is analogous to before. This is because the real value of exposure decreases in p in both versions of the model.

Corollary 3. *When the capital constraint is relaxed so that* λ *decreases, demand becomes flatter, the market price increases and price impact increases.*

A.2 Discriminatory price auction

So far, we have assumed that the market clears via a uniform price auction. While this auction format nicely approximates market clearing in many markets, including U.S. Treasury auctions and exchange trading, it does not fit all settings. Sometimes, bidders (or traders) do not pay the market clearing price for each unit won at auction, but the prices that they offered to pay for these units. This is known as discriminatory pricing and it is the case in our empirical setting, as well as other primary markets for government bonds (e.g., Brazil, France, Italy, U.K., Mexico).

To ensure that the model predictions that we derive below hold for uniform price and discriminatory price auctions, and to derive equilibrium conditions for our calibration, we derive an equilibrium in a discriminatory price auction. When bidders

have private information and demand multiple units, this is a challenging problem that the literature has not yet solved. The reason is that the equilibrium depends on the bidders' beliefs on where the market clears since bidders pay the prices that they bid rather than the market clearing price.

To achieve tractability, we make two changes to the setting. First, we rely on the fact that $v_i(a) = \frac{\sigma\rho}{1+\lambda\kappa}[\mu - (z_i + a)]$ is a dealer's true willingness to pay for amount a given objective function (1) and shadow cost of capital $\lambda \geq 0$ (explained in Section 5.1) and let the dealer's willingness to pay equal to that. z_i is the dealer's private information. It is drawn from iid across i from a distribution with support $[\underline{z}, \overline{z}]$.

Second, we impose that the amounts that bidders win in the auction follow a Generalized Pareto Distribution.[20] Formally, winning quantities are drawn from a distribution with CDF $F_i(a) = 1 - (\frac{\nu_i + \xi a}{\nu_i})^{-\frac{1}{\xi}}$ with $\xi \in (-\infty, -1], \nu_i = -\xi(\frac{N(1-\xi)-1}{N(1-\xi)})(\overline{z} - z_i) - \xi(\frac{A}{N})$. Proving existence and characterizing an equilibrium for discriminatory price auctions for other distributions of winning quantities is an open question in the literature, and beyond the scope of this paper.

Proposition 3. *There exists an equilibrium in which dealer i submits the demand curve*

$$a_i(p) = \left(\frac{N(1-\xi)-1}{N-1}\right)\frac{1}{\sigma\rho}\left(\mu_i - (1+\lambda\kappa)p\right)$$

with $\mu_i = \mu + \frac{\rho\sigma}{1-\xi}(\overline{z} - z_i) + \frac{\rho\sigma A}{N(1-\xi)-1}$ *as long as* $\mathbb{E}[\mu_i] \geq \frac{\rho\sigma A(N-1)}{N(N(1-\xi)-1)}$.

The key insight for this paper is that the equilibria of both the uniform price and discriminatory price auction formats have a similar functional form. The intuition for this equilibrium is similar to the intuition for the equilibrium in a uniform price auction. The main difference is that bidders form different expectations over how much they benefit and how much they must pay when winning an additional unit than in equation (5). For more details, see Ausubel et al. (2014) who describe the trade-off in a framework without private information.

[20] This assumption implies functional form restrictions on the model's exogenous primitives that cannot be easily summarized, which is why we state the assumption based on the (endogenous) distribution of winning quantities.

B Proofs

B.1 Propositions

Proof of Proposition 1. Given dealer i has CARA utility and $R \sim N(\mu, \sigma)$, dealer i maximizes

$$\max_p \left\{ \mu[a_i + z_i] - \frac{\rho\sigma}{2}[a_i + z_i]^2 - q_i p - \lambda_i [E_i - \kappa p(a_i + z_i)] \right\}$$

for a given a_i. Take pointwise FOC w.r.t. a_i for each realization of p

$$\begin{aligned} \mu - \rho\sigma[a_i + z_i] &= (1 + \lambda_i\kappa)(p + \Lambda_i a_i) \\ a_i(p) &= ((1 + \lambda_i\kappa)\Lambda_i + \sigma\rho)^{-1}(\mu - \sigma\rho z_i - (1 + \lambda_i\kappa)p), \end{aligned}$$

where $\Lambda_i = \frac{\partial p}{\partial a_i}$. In equilibrium, trader i's true price impact equals to the slope of his inverse residual supply curves, i.e., for each i,

$$\Lambda_i = -\left(\sum_{j \neq i} \frac{\partial a_j(\cdot; \lambda_j)}{\partial p} \right)^{-1}.$$

In equilibrium, all dealers submit best replies to each other. Therefore, given $a_j(p) = ((1 + \lambda_j\kappa)\Lambda_j + \sigma\rho)^{-1}(\mu - \sigma\rho z_j - (1 + \lambda_j\kappa)p)$, Λ_i is

$$\Lambda_i = \left(\sum_{j \neq i} ((1 + \lambda_j\kappa)\Lambda_j + \sigma\rho)^{-1}(1 + \lambda_j\kappa)) \right)^{-1} = \left(\sum_{j \neq i} (\Lambda_j + \frac{\sigma\rho}{1 + \lambda_j\kappa})^{-1} \right)^{-1}$$

By Malamud and Rostek (2017) Proposition 1,

$$\Lambda_i = \beta_i \alpha_i \sigma \text{ with } \beta_i = \frac{2}{\alpha_i b - 2 + \sqrt{(\alpha_i b)^2 + 4}} \text{ and } \alpha_i = \frac{\rho}{1 + \lambda_i\kappa},$$

where $b \in \mathbb{R}^+$ is the unique positive solution to $1/2 = \sum_i (\alpha_i b + 2 + \sqrt{(a_i b)^2 + 4})^{-1}$. Further, Λ_i decreases monotonically in λ_i.

The Lagrange multipliers, λ_i's, are such that

$$E_i = \kappa p^*[a_i(p^*) + z_i] \ \forall i, \text{ where } p^* = \frac{\sum_i((1+\lambda_i\kappa)\Lambda_i + \sigma\rho)^{-1}(\mu - \sigma\rho z_i) - A}{\sum_i((1+\lambda_i\kappa)\Lambda_i + \sigma\rho)^{-1}(1+\lambda_i\kappa)} \quad \square$$

Proof of Proposition 2. Take the perspective of dealer i and assume all others play the equilibirum. Dealer i maximizes

$$\mathcal{L}(p, \lambda_i) = \mu(a_i + z_i) - \frac{\rho\sigma}{2}(a_i + z_i)^2 - a_i p - \lambda_i(E - \kappa p\eta(p))$$

pointwise w.r.t. a_i for each p. Let $\Lambda_i = \frac{\partial p}{\partial a_i}$. Then the necessary condition is

$$\begin{aligned} 0 &= \mu - \rho\sigma[a_i + z_i] - (p + \Lambda_i a_i) + \Lambda_i\lambda_i\kappa\left[(\alpha - \beta p) - p\beta\right] \\ a_i(p) &= (\Lambda_i + \sigma\rho)^{-1}\Big(\mu + \alpha\kappa\Lambda_i\lambda_i\kappa - \sigma\rho z_i - (1 + 2\beta\kappa\Lambda_i\lambda_i)p\Big) \end{aligned} \tag{13}$$

The necessary condition is sufficient as long as

$$-a_i(\rho\sigma + \Lambda_i) > 0 \Leftrightarrow \rho\sigma + \Lambda_i > 0 \text{ given } a_i \geq 0.$$

In equilibrium everyone must play best responses to one another, so that

$$\Lambda_i = \left(\sum_{j\neq i} \frac{1 + 2\beta\kappa\Lambda_j\lambda_j}{\sigma\rho + \Lambda_j}\right)^{-1}$$

When $E_i = E$ for all i, we conjecture that there is an equilibrium in which all dealers are equally constraint: $\lambda_i = \lambda$. This implies $\Lambda_i = \Lambda$. Thus, all dealers submitting demand functions (13) with $\Lambda_i = \Lambda$ such that

$$\begin{aligned} \frac{1}{\Lambda} &= (N-1)(1 + 2\beta\kappa\Lambda\lambda)(\Lambda + \sigma\rho)^{-1} \\ \Leftrightarrow \Lambda &= \frac{-(N-2) + \sqrt{(N-2)^2 + 8\beta\kappa\lambda(N-1)\rho\sigma}}{\sqrt{4\beta\kappa\lambda(N-1)}} \end{aligned} \tag{14}$$

and $\lambda_i = \lambda$. We call the equilibrium guess $a_i^{guess}(\cdot)$.[21]

[21]Note that there are two solutions for Λ but only one can be positive given parameter restrictions.

To show that this equilibrium exists, assume that all dealers but i play this equilibrium. We need to show that dealer i's best reply is to play that equilibrium as well. Dealer i's best response to all others playing the equilibrium guess is

$$a_i(p) = (\Lambda + \sigma\rho)^{-1}\Big(\mu + \alpha\kappa\Lambda\lambda_i - \sigma\rho z_i - (1 + 2\beta\kappa\Lambda\lambda_i)p\Big)$$

with Λ given above. Given this best reply and the fact that all other dealers play the equilibrium guess, the market would clear at p^{BR}. The capital constraint

$$E - \kappa p^{BR}\eta(p^{BR}) = 0 \text{ where } a_i(p^{BR}) + \sum_{j\neq i} a_j^{guess}(p^{BR}) = A$$

pins down a relation between λ_i and λ, call this relation $\lambda_i(\lambda)$. The guessed equilibrium exists if there is a fixed point $\lambda_i(\lambda) = \lambda$ our equilibrium exists. For a given Λ in (14), one can show that there are two solutions at which $\lambda_i(\lambda) = \lambda$, but only one of them is positive:

$$\lambda = \frac{-\kappa(4\beta E + \alpha^2 k)\Lambda N + \sqrt{\kappa^3(4\beta E + \alpha^2 k)\Lambda^2(-\alpha N - 2\beta(-\mu N + A(\Lambda + \rho\sigma) + \rho\sigma\sum_i z_i))^2}}{2\beta\kappa^2(4\beta E + \alpha^2\kappa)\Lambda^2 N}$$

When $\alpha = 0$, λ is such that

$$E\Big(N^2(N + \sqrt{(N-2)^2 + 8\beta\kappa\lambda(N-1)\rho\sigma})^2\Big) =$$
$$4\beta\kappa(N-1)^2\Big(-N\mu + A\rho\sigma + \frac{A(2 - N\sqrt{(N-2)^2 + \beta\kappa\lambda(N-1)\rho\sigma})}{4\beta\kappa\lambda(N-1)} + \rho\sigma\sum_i z_i\Big)^2$$

Take the square root on both sides

$$\sqrt{E}\Big(N(N + \sqrt{(N-2)^2 + 8\beta\kappa\lambda(N-1)\rho\sigma})\Big) =$$
$$2\sqrt{\beta\kappa}(N-1)\Big(-N\mu + A\rho\sigma + \frac{A(2 - N\sqrt{(N-2)^2 + \beta\kappa\lambda(N-1)\rho\sigma})}{4\beta\kappa\lambda(N-1)} + \rho\sigma\sum_i z_i\Big)$$

This can be solved for λ. Thus there is a λ. This λ should be positive for sufficiently low κ. □

Proof or Proposition 3. We follow Wittwer (2018) who proves existence of an equilibrium in an auction with random supply. The proof of Corollary 1 and Theory 2 go through when supply is fixed. To adjust these proofs to our setting, it suffices to replace $\overline{Q}$ with A and t_i by $\mu - \sigma\rho z_i$. Further, we must invert the bidding function so that it becomes a demand function: $a_i(p) = \left(\frac{N(1-\xi)-1}{N-1}\right)\frac{1}{\sigma\rho}\left(\mu_i - (1+\kappa s)p\right)$. □

B.2 Corollaries

Proof of Corollary 1. Let all λ_i's decrease, which happens, for instance, when κ_i's decrease. By Malamud and Rostek (2017) Proposition 1, Λ_i is monotonically increasing in α_i, which implies that it is decreasing in λ_i.

To show that $a_i(\cdot)$ of all i become flatter, which mechanically increases the market clearing price, fix one dealer i. Take the derivative w.r.t. p and then w.r.t. λ_i:

$$\frac{\partial a_i(p)}{\partial p} = -\frac{1+\lambda_i\kappa_i}{(1+\lambda_i\kappa_i)\Lambda_i + \sigma\rho_i}$$
$$\frac{\partial}{\partial\lambda_i}\frac{\partial a_i(p)}{\partial p} = \frac{-\kappa_i\rho\sigma + (1+\lambda_i\kappa_i)^2\frac{\partial\Lambda_i}{\partial\lambda_i}}{(\rho\sigma + \Lambda_i + \kappa_i\lambda_i\Lambda_i)^2} \leq 0$$

given that $\frac{\partial\Lambda_i}{\partial\lambda_i} \geq 0$ and $\kappa_i\rho\sigma \geq 0$.Thus when λ_i decreases, the negative slope increases towards 0, which means that demand becomes flatter.

The markup is defined as the absolute value of the difference between the price at which the market would clear if dealers were price-taker and the price it clears when they have market power. Let $p^*(\Lambda_i)$ denote the price at which the market clears when dealers have market power and $p^*(0)$ when they are price-takers, then

$$markup = p^*(0) - p^*(\Lambda_i)$$
$$\text{with } p^*(\Lambda_i) = \frac{\sum_i((1+\lambda_i\kappa)\Lambda_i + \sigma\rho)^{-1}(\mu - \sigma\rho z_i) - A}{\sum_i((1+\lambda_i\kappa)\Lambda_i + \sigma\rho)^{-1}(1+\lambda_i\kappa)}$$

as we have shown when proving Proposition 1. When λ_i decreases, the markup increases because $p^*(0)$ increases more than $p^*(\Lambda_i)$. □

Proof of Corollary 2. Let dealers be ex-ante identical. The equilibrium in a uniform price auction is given by Proposition 1 (ii), and in a discriminatory price auction by Proposition 3.

Let $p^*(\Lambda)$ denote the price at which the market clears when dealers have market power and $p^*(0)$ when they are price-takers, and consider the uniform price auction first. The market clears at $p^*(\Lambda) = \frac{1}{1+\lambda\kappa}\left(\frac{1}{N}\sum_i \mu_i - \frac{N-1}{N-2}\frac{A}{N}\sigma\rho\right)$ with $\mu_i = \mu - \sigma\rho$. To derive the markup, we first compute at which the market would clear if all bidders were price-takers, that is submit demand curves $a_{iT}^* = limit_{N\to\infty} a_i^*(p)$. Then $p^*(0) = \frac{1}{1+\lambda\kappa}\left(\frac{1}{N}\sum_i \mu_i - \frac{A}{N}\rho\sigma\right)$. With this,

$$markup = p^*(0) - p^*(\Lambda) = \frac{1}{1+\lambda\kappa}\left(\frac{A}{N}\right)\left(\frac{1}{N-2}\right)\rho\sigma$$

Analogously, we can derive the expression for the discriminatory price auction, in which the market clears at $p^* = \frac{1}{1+\lambda\kappa}\left(\frac{1}{N}\sum_i \mu_i - \sigma\rho\left(\frac{N-1}{N(1-\xi)-1}\right)\frac{A}{N}\right)$ with μ_i as specified in Proposition 3. Here $p^*(0) = \frac{1}{1+\lambda\kappa}(\mu + \frac{\rho\sigma}{\xi-1}(\frac{A}{N} + \frac{1}{N}\sum_i z_i - \xi\overline{z}))$. With this,

$$markup = p^*(0) - p^*(\Lambda) = \frac{1}{1+\lambda\kappa}\left(\frac{A}{N}\right)\left(\frac{\xi}{\xi-1}\right)\rho\sigma.$$

Note that in the uniform price auction, $markup(\lambda)$ is the average amount of shading at market clearing, $\frac{1}{N}\sum_i shading(a_i^*)$, where $shading(a_i^*)$ is the difference between the price bidder i offer for amount a_i^* if she were price-taking and the price she actually offers. In a discriminatory auction, the markup differs from the average amount of shading at market clearing.

Given these expressions, it follows that

$$\eta = \frac{\partial markup}{\partial\lambda\kappa}\frac{\lambda\kappa}{markup} = \frac{\partial p^*}{\partial\lambda\kappa}\frac{\lambda\kappa}{p^*} = \frac{1}{1+\lambda\kappa} - 1. \quad \square \tag{11}$$

Proof of Corollary 3 (i) The slope in the demand function is

$$\frac{\partial a_i(p)}{\partial p} = -\frac{N-2+\sqrt{(N-2)^2 + 8\beta\kappa\lambda(N-1)\rho\sigma}}{2(N-1)\rho\sigma} <\Leftrightarrow \beta > \frac{-4+4N-N^2}{-8\kappa\lambda\rho\sigma + 8\kappa\lambda N\rho\sigma}$$

The slope decreases in λ if $\lambda > 0$ and $\beta > 0$, and increases in λ if $\frac{-4+4N-N^2}{-8\kappa\lambda\rho\sigma+8\kappa\lambda N\rho\sigma} < \beta < 0$ and $\lambda > 0$. Thus, when $\beta > 0$ and the constraint is relaxed so that λ decreases, the negative slope increases towards 0, meaning that demand becomes flatter.

When demand functions become flatter, the market price must increase ceteris paribus.

(ii) It is straightforward to show that Λ decreases in λ when $\beta > 0, \lambda > 0$, and increases in λ when $\frac{-4+4N-N^2}{-8\kappa\lambda\rho\sigma+8\kappa\lambda N\rho\sigma} < \beta < 0$ and $\lambda > 0$. □

C Model estimates per maturity class

[in progress]

Appendix Table 4: Bid functions are approximately linear

	mean	median	sd
β_t	0.20	0.17	0.11
R_t^2	0.82	0.83	0.16
Adj. R_t^2	0.77	0.77	0.21
Within R_t^2	0.53	0.54	0.15

Appendix Table 4 shows the point estimate and R^2 from regressing bids on quantities in each auction: $b_{ti\tau k} = \zeta_{ti\tau} + \beta_t q_{ti\tau k} + \epsilon_{ti\tau k}$. The subsample are bidding-functions with at least 2 steps. Bids are in yields (bps) and quantities in percentage of supply.

Appendix Figure A1: Holders of Canadian government bonds

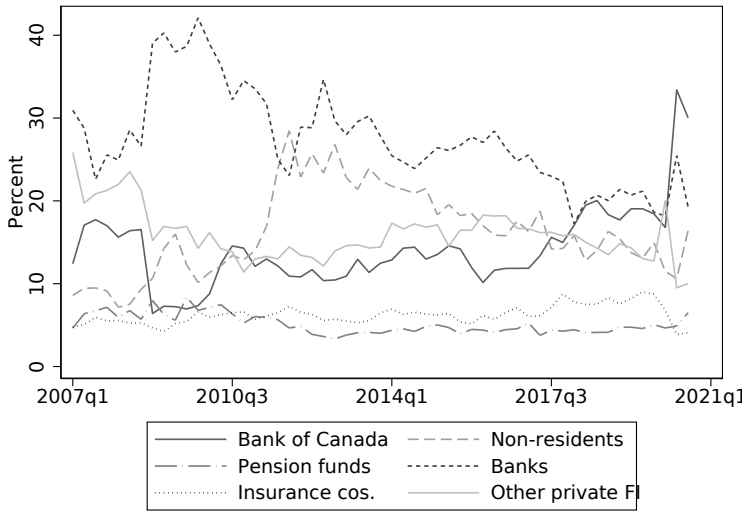


Figure A1 shows who holds Canadian government bonds and bills from 2007 until 2021 in percentage of par value outstanding: Bank of Canada, Non-residents, Canadian pension funds, Canadian banks, Canadian insurance companies, and other private firms. The banks' holdings are mostly driven by the eight banks we focus on. They hold over 80% of the assets.

Appendix Figure A2: Change in the slope using LR

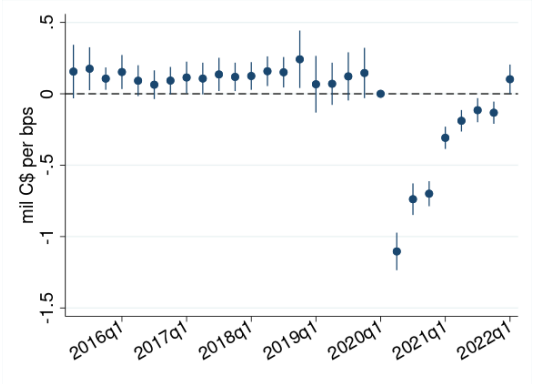
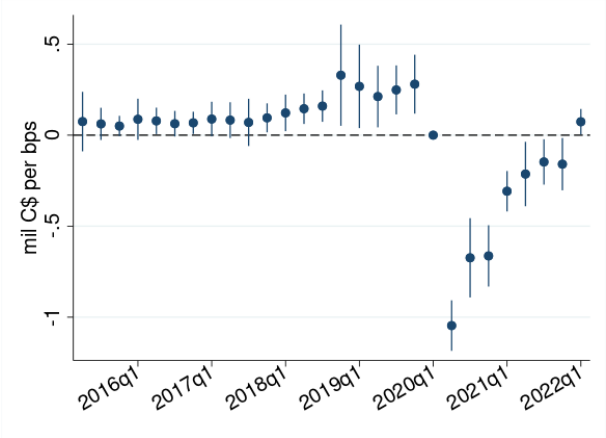


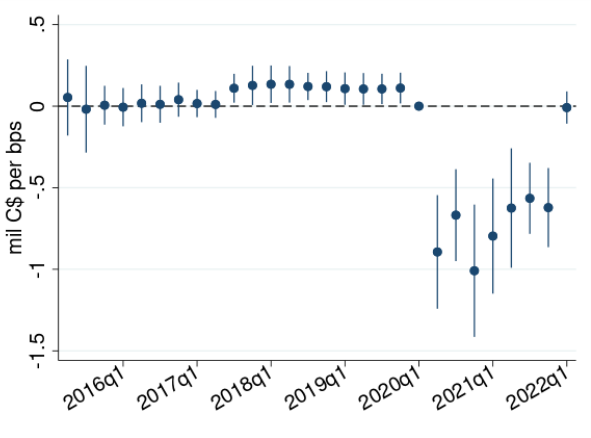
Figure A2 shows the γ_k estimates and 95% confidence intervals of the regression (7): $slope_{iqs} = \alpha + \sum_{k=-K}^{K} \gamma_k * D_k * LR_{ik} + \zeta_{qs} + \epsilon_{iqs}$. All magnitudes are relative to the benchmark in 2020q1. The slopes are measured in million C$ per bps, leverage ratios are in bps.

Appendix Figure A3: Change in the slope with dealer fixed effects

(a) Using LR



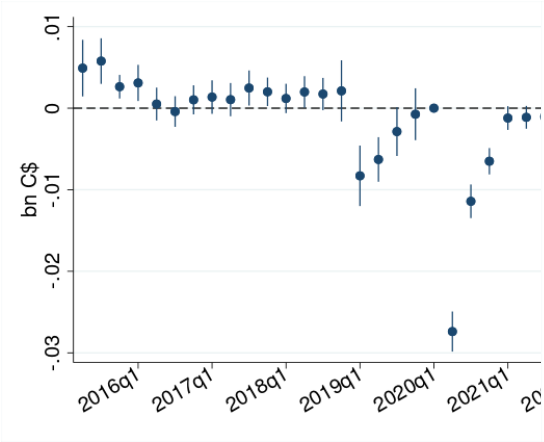
(b) Using supervisory LR thresholds



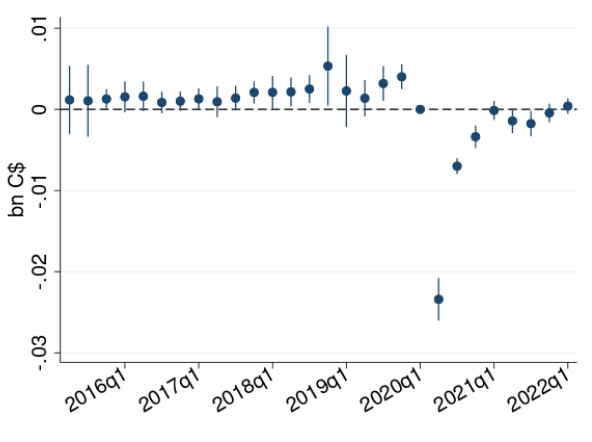
Appendix Figure A3a shows the γ_k estimates and 95% confidence intervals of the regression (7): $slope_{iqs} = \alpha + \sum_{k=-K}^{K} \gamma_k * D_k * LR_{ik} + \zeta_{qs} + \zeta_i + \epsilon_{iqs}$. Appendix Figure A3b replaces LR_{ik} by the institution-specific Basel III threshold. All magnitudes are relative to the benchmark in 2020q1. The slopes are measured in million C$ per bps, thresholds and leverage ratios are in bps. Standard errors are clustered on the dealer level.

Appendix Figure A4: Event study with maximal demand, i.e., $\max_k\{a_{i,t,s,k}\}$

(a) Without dealer fixed effect

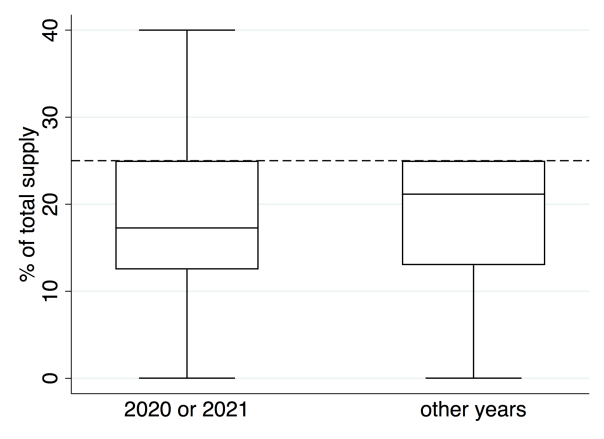


(b) With dealer fixed effect



Appendix Figure A4a shows the γ_k estimates and 95% confidence intervals of the regression (7): $a_max_{iqs} = \alpha + \sum_{k=-K}^{K} \gamma_k * D_k * LR_{ik} + \zeta_{qs} + \epsilon_{iqs}$ with a_max_{iqs} as average of $\max_k\{a_{itsk}\}$ per a dealer/quarter/security. In Appendix Figure A4b, we add a dealer fixed effect. Demand is measured in billion C$. Standard errors are clustered at the dealer level in (b).

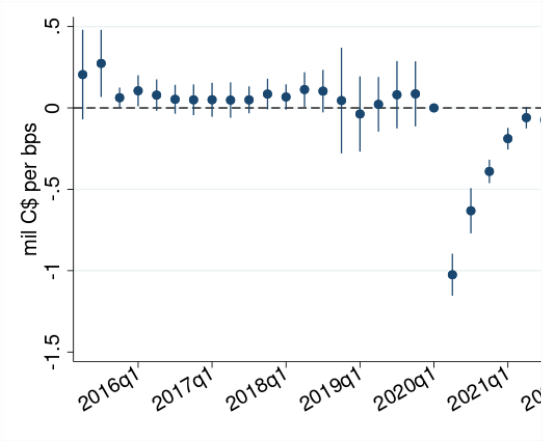
Appendix Figure A5: Maximal dealer demand as % of total supply



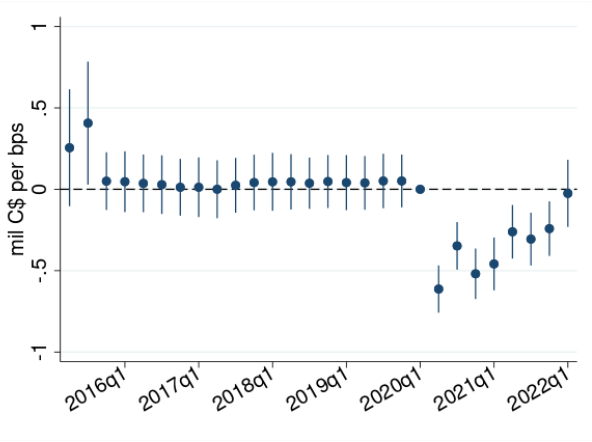
Appendix Figure A5 shows box plots of how much the average dealer demanded in an auction in 2020 or 2021 and all other years as % of auction supply. The dashed line represents the maximal bidding limit in regular times. It was increased to 40% during 2020/2021. The minimal bidding limits, which must not be met at each auction, are around 10% for most banks.

Appendix Figure A6: Event study with unconstrained dealers (w.r.t. bidding limits)

(a) With LR

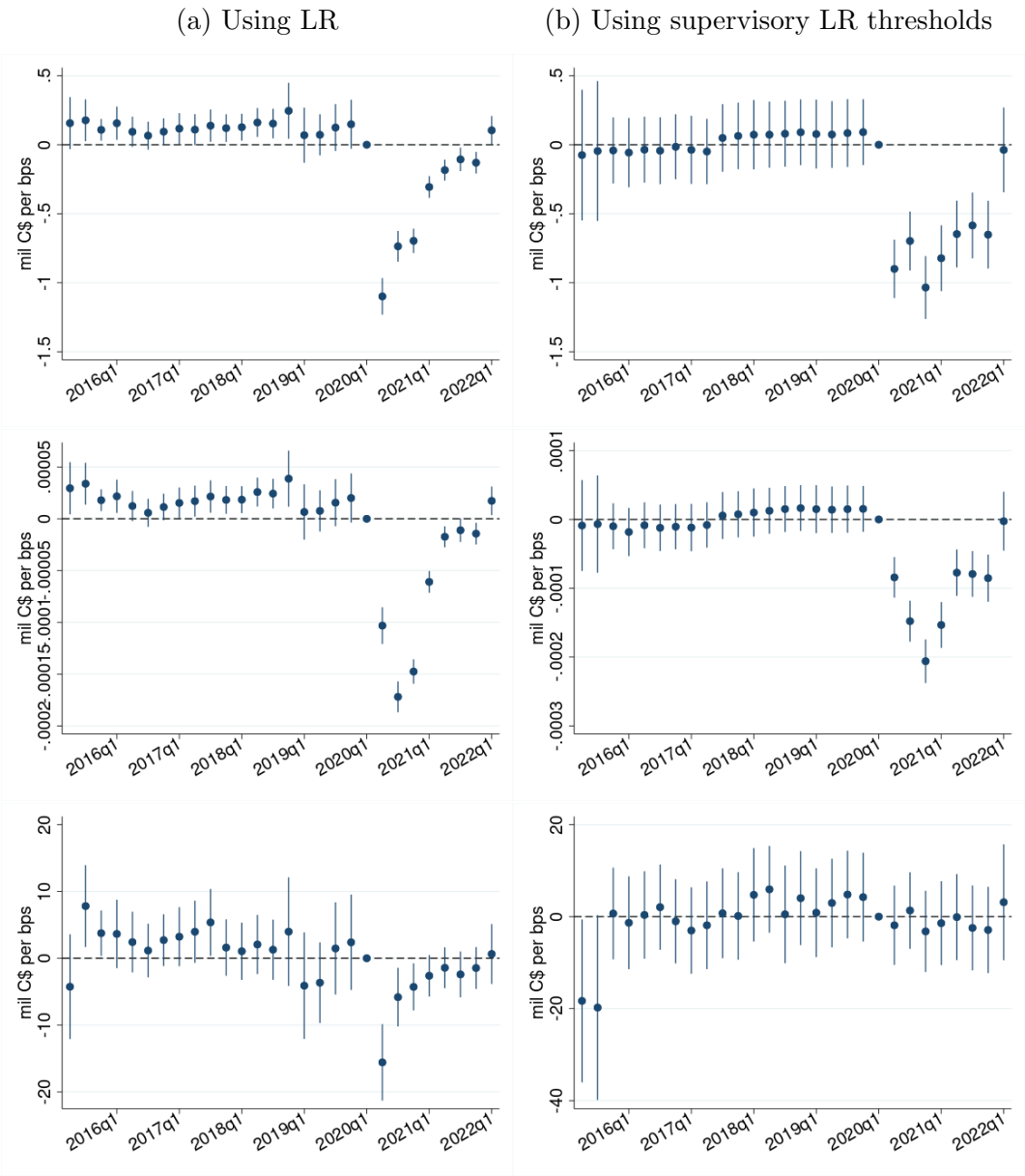


(b) With supervisory LR thresholds



Appendix Figure A6 is analogous to Figure 4 combined with Appendix Figure A2. It shows the γ_k estimates and 95% confidence intervals of the regression (7): $slope_{iqs} = \alpha + \sum_{k=-K}^{K} \gamma_k * D_k * LR_{ik} + \zeta_{qs} + \epsilon_{iqs}$. Figure 4 replaces LR_{ik} by the institution-specific Basel III threshold. All magnitudes are relative to the benchmark in 2020q1. The slopes are measured in million C$ per bps, leverage ratios and thresholds are in bps.

Appendix Figure A7: Event study with alternative slope measures



Appendix Figure A7 is analogous to Figure 4 combined with Appendix Figure A2, but uses different slope measures. It shows the γ_k estimates and 95% confidence intervals of the regression (7): $slope^{other}_{iqs} = \alpha + \sum_{k=-K}^{K} \gamma_k * D_k * LR_{ik} + \zeta_{qs} + \epsilon_{iqs}$ in (a) and with supervisory LR thresholds instead of LRs in (b) for different alternative slope measures. In the first row, we replace $\max_k\{a_{itsk}\}$ in (6) by the demand at the dealer asked for at the highest step it ever won. In the second row, we cap this amount by the largest amount ever won (in % of supply). In the third row, we use a local slope measure. For this, we first find the market clearing yield of an auction, $yield^C_{ts}$. Then, we leverage the fact that, according to the auction rules, bid yields cannot have more than three decimal places. We determine the yield that lies just above, $yield^{UB}_{ts} = yield^C_{ts} + 0.001$, and the yield that lies just below the clearing yield: $yield^{LB}_{ts} = yield^C_{ts} - 0.001$. With this, we compute the local slope as the difference in the demand of a dealer at these two cutoff yields over the difference in the cutoff yields. All magnitudes are relative to the benchmark in 2020q1. The slopes are measured in million C$ per bps, leverage ratios and thresholds are in bps. All graphs look similar when we include dealer fixed effects.