Intermediary asset pricing: Capital constraints and market power*

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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 increase the market price and the degree of price manipulation 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 reduces bond yields but increases manipulation by 47% each. This implies lower debt funding costs at an implicit cost of higher price distortion.

Keywords: Financial intermediaries, asset demand, asset prices, government bonds, capital requirements, leverage ratios

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

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1 Introduction

What moves asset demand and 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, referred to as dealers (e.g., Brunnermeier and Pedersen (2009); He and Krishnamurthy (2012, 2013); Brunnermeier and Sannikov (2014)). These dealers are the marginal buyers in many asset markets. In practice, they face intermediary costs (such as capital constraints, balance sheet costs and limited risk-bearing capacity) on the one hand. On the other hand, they likely enjoy some market power given that there is only a handful of them in many markets. This stands in contrast to the classic view that markets are highly competitive, motivating the assumption of perfect competition in models of intermediary asset pricing.

We study how dealer (equity) 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 transaction-level data on Canadian Treasury auctions—in which dealers submit entire demand curves—by leveraging financial market events and regulatory responses during the COVID-19 pandemic.

In the model, risk-averse dealers compete to buy multiple units of an asset that pays out an uncertain return in the future. 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 how many 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. While the auction is ongoing, each dealer-bank organizes funding for the auction purchase. It can either issue new debt or new equity, but faces a capital constraint

[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)).

that affects the split between debt and equity financing. This, in turn, affects the dealer's demand because increasing capital (relative to debt) is costly.[2]

We show that there is a unique linear equilibrium in which each dealer's demand depends on how much capital the dealer-bank holds and the size of the capital cost. The key prediction of the model is that demand (which map prices into quantities) becomes flatter when capital costs decrease as it becomes cheaper to buy larger amounts of the asset. As a result, unless there are adjustments in supply, an asset's market price increases.[3] 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 the 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 (rather than the subsidiary level following

[2]The literature has identified various reasons for which raising equity instead of debt may be costly, including forgone tax deductions on debt, debt overhang, agency costs, asymmetric information (e.g., Myers (1977); Myers and Majluf (1984); Gertler et al. (2012); Gornall and Strebulaev (2018); Andersen et al. (2019)). We show that the capital cost can be interpreted as shadow cost (i.e., Lagrange multiplier) of a binding capital constraint. For a literature survey on financial intermediation, including banking under capital constraints, see Gorton and Winton (2003).

[3]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.

He et al. (2017)). We observe all winning and losing bids, in addition to institution-specific regulatory capital thresholds, and the Basel III Leverage Ratio (LR) of each dealer-bank. The LR must be at least 3% and therefore acts as a constraint on bank-capital. The LR is the Canadian equivalent to the Supplementary Leverage Ratio (SLR) in the U.S. It is reported quarterly and measures a bank's Tier 1 capital relative to its total leverage exposure.[4]

With the data, we gather evidence in favor of the model's predictions. For this, we leverage a policy intervention during the COVID-19 pandemic. To buffer against negative effects of the pandemic, there was a large increase in fiscal expenditures, financed by an increase in government bonds. Government bonds were exempted from the LR in April 2020 until December 2021. During this period, dealers could buy government bonds without having to increase their capital positions in order to fulfill Basel III capital requirements. An event study confirms our hypothesis 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. In theory, this increases both the market price and price manipulation, but empirically, these effects are hard to identify.

We leverage our model to quantify by how much the market price and price manipulation change as capital costs change. We proceed in two steps to pin down the two main model parameters, the banks' degree of risk aversion and the capital cost. First, we rely on estimation techniques from the auctions literature (introduced by Guerre et al. (2000); Hortaçsu and McAdams (2010); Kastl (2011)) to estimate how much bidders manipulate the price, i.e., shade their bids. Unlike using bids directly, this gives us an estimate of the per-auction extent of price manipulation, which depend, among observables, on the degree of bank risk aversion and the cost of capital. Second, we use the insight that price manipulation changes when capital

[4]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.

costs change combined with the policy changes of the LR that eliminated and then reintroduced capital costs, to back out two capital cost values. The magnitude of the price manipulation in the absence of capital costs pins down the banks' risk aversion.

We find that banks are close to risk-neutral but face sizable capital costs. This is reassuring given that these are global banks who can diversity away most types of risk. The cost parameters imply that the market yield and the amount of price manipulation increases by 0.47%–0.55% if the capital cost increases by 1%. In comparison, the estimate of an OLS regression of auction yields on LR, which we suspect to be upward biased due to endogeneity, implies that a 1% increase in LR increases the yield by roughly 0.57%–0.78%. Since we do not use the regression information to estimate the model and yet get similar (but unbiased) elasticities, validates 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 yield manipulation of 47% each. This translates into higher auction revenues and thus savings for the government at an implicit cost of larger price 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 price 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)).[5] 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)).[6]

The key difference to all these models is that we zoom in on the intermediary financial sector and allow dealers to a have price impact due to market power in the tradition of Kyle (1989). The market clears via a multi-unit auction (as in Vayanos (1999); Vives (2011); Rostek and Weretka (2012); Malamud and Rostek (2017); Wittwer (2021)). However, unlike existing theories which analyze the auction itself, we look at a bigger game that includes the decision on how to fund the auction purchase.

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)).[7] Most existing studies use market-level data, such as

[5]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.

[6]Other examples of balance sheet usage costs include the cost of collateralizing liabilities (e.g., Johannes and Sundaresan (2007)), the cost of value-at-risk constraints (e.g., Adrian and Brunnermeier (2016); Brownlees and Engle (2017)).

[7]More remotely related strands of the literature build on insights from theories with constrained intermediaries to propose measures for market liquidity or economic activities (e.g., Gilchrist and Zakrajšek (2012); Nagel (2012); Hu et al. (2013)), to study trading and pricing behavior during the financial crisis of 2007–2009 (e.g., Ben-David et al. (2011)), to assess whether financial regulation decreases the ability of dealers to intermediate trades

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 capital cost 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).[8]

Outline. The remainder of the paper is structured as follows: Section 2 introduces the model and derives predictions. We test these predictions in Section 4 after describing the institutional setting and the data in Section 3. In Section 5, we calibrate the model and conduct counterfactuals. Section 6 concludes. All proofs are in the appendix. Throughout all sections, we omit the word "equity" when describing "equity capital" or related adjectives and verbs.

2 Model

A natural place to start to explain what drives asset demand is the workhorse model by He and Krishnamurthy (2012, 2013). This model is missing, however, two ingredients that have become increasingly important. The first is a regulatory capital constraint in the spirit of Basel III. The second ingredient is imperfect competition in the intermediation sector, which is supported by a large body of empirical work.

In Appendix B we present a model of the intermediary sector with these new

(e.g., Adrian et al. (2017a,b)), or to discover mis-pricing (e.g., Du et al. (2018); Fleckenstein and Longstaff (2020)).

[8]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.

elements. Certain features of this model, however, do not directly map to our data. For instance, we observe that banks target capital levels that are above the regulatory capital constraint.[9] We therefore present a framework in which banks have capital targets that are costly to maintain rather than binding capital constraints. Crucially, the model's predictions we derive are general in that they hold in all settings that we consider, including our modified model of He and Krishnamurthy (2012, 2013).

To further highlight the generality of our results, we consider different market clearing mechanisms. In our benchmark, we model market clearing via a uniform price auction in which banks submit demand schedules and all winners pay the price at which aggregate demand meets aggregate supply. Such an auction can be one-sided, meaning that bidders buy but not sell, or double-sided, so that bidders buy and sell. In practice, many primary markets clear via a uniform price auction (such as the primary market for government debt in the U.S.), while trading on an exchange can be approximated via a double-sided uniform price auction (e.g., Kyle (1989)). In a model extension, we let the market clear via a discriminatory price auction in which winning bidders pay the prices that they offered, not the market clearing price. Such an auction is used to sell government debt in many countries, including Canada.

Market players. There are $N > 2$ dealers, which each belong to a bank. Dealers buy assets in competition with one another, while their bank organizes funding for the auction purchase. Equivalently, one may think of the dealer plus its bank as the same player. We separate the two because it makes the transition to the empirical application—where trading decisions are made by a trading-desk (the dealer), but capital requirements must be met at the company holding level (the bank)—smoother. However, to highlight that the dealer and its bank belong together, we use the same superscript i for a dealer-bank pair.

Dealer demand at auction. Dealers bid in a uniform price auction to buy units of an asset of total supply $A > 0$. Alternatively, we could let dealers trade in a double

[9]Similarly, 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.

auction with $A \in \mathbb{R}$.

One unit of the asset pays $R \sim N(\mu, \sigma)$ in the future. The risk can come from various sources, depending on the type of asset. In our empirical application, where the asset is a government bond, R represents the return from selling the bond in the secondary market and dealers are averse to interest rate and inflation risk.

Dealers differ in how much of the asset they hold in inventory, z_i, when bidding in the auction. The inventory position is a by-product of the dealer's cash trades with clients that are outside of our model. It is private information to the dealer, and drawn *iid* from a distribution with mean $z \in \mathbb{R}$.[10] In a cash trade—which realizes, for instance, in the when-issued market—the dealer exchanges the asset for cash, or vice versa. For simplicity, the per-unit price of a cash trade, $\psi \in \mathbb{R}^+$, is exogenous and commonly known.

In a uniform price auction, each dealer submits a demand schedule that is continuous and strictly decreasing:

$$a_i(\cdot) : \mathbb{R} \to \mathbb{R}.$$

It specifies how many units of the asset, $a_i(p)$, the dealer seeks to buy for each price, p. For a given price p, 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:

$$\pi_i(a_i, p) = \mathbb{E}\left[1 - \exp\Big(-\rho\omega_i(a_i, p)\Big)\right]. \tag{1}$$

Here, $\rho > 0$, measures the dealer's degree of risk-aversion, which, for simplicity, is commonly known among dealers. The future wealth, $\omega_i(a_i, p)$, is equal to the asset payoff, R, net of the prices paid, p and ψ, and a capital cost that we explain below:

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

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, $a_i^* = a_i(p^*)$.

[10]The independence assumption is for simplicity, and can be relaxed.

Table 1: Bank's initial, expected and actual balance sheet after the auction

(a) Initial balance sheet before the auction

Assets		Liabilities	
Cash/Reserves	1	Debt	$1 - \kappa_0$
Bonds	0	Capital	κ_0

(b) Expected balance sheet after the auction

Assets		Liabilities	
Cash/Reserves	$1 - \mathbb{E}[\psi z_i]$	Debt	$(1 - \kappa_0) + (1 - \kappa_i)\mathbb{E}[p^* a_i^*]$
Bonds	$\mathbb{E}[p^* a_i^*] + \mathbb{E}[\psi z_i]$	Capital	$\kappa_0 + \kappa_i \mathbb{E}[p^* a_i^*]$

(c) Actual balance sheet after the auction

Assets		Liabilities	
Cash/Reserves	$1 - \psi z_i$	Debt	$(1 - \kappa_0) + (1 - \kappa_i) p^* a_i^*$
Bonds	$p^* a_i^* + \psi z_i$	Capital	$\kappa_0 + \kappa_i p^* a_i^*$

Table 1 shows three balance sheets. (a) is the bank's initial balance sheet, which is common across all banks. (b) is the balance sheet the bank expects to have at the end of the game. This is after its dealer wins a_i^* of the asset at price p^* and exchanges z_i of the asset at price ψ for cash, given a fraction κ_i of the total auction purchase is financed with new capital and the remaining fraction is financed via new debt (e.g., in form of deposits). (c) displays how the balance sheet actually looks at the end of the game.

Bank's funding choice. Before the dealer bids in the auction, the bank collects money that it expects to use to pay for the asset. It can issue debt or capital but faces a capital constraint. Initially, it holds $\kappa_0 \geq 0$ in capital and $1 - \kappa_0$ in debt; the cash/reserve holdings are normalized to 1. Given this initial balance sheet—which is common across banks and shown in Table 1 (a)—a bank decides what fraction, $\kappa_i \in (0, 1)$, of the total expected auction payment, $\mathbb{E}[p^* a_i^*]$, that it finances via additional capital and what fraction via new debt. In choosing κ_i, the bank's goal is to bring its capital ratio after the auction purchase to the regulatory target level $\kappa^* \in [0, 1)$.[11]

Increasing capital to fulfill the capital requirement is costly: each unit of capital costs $s \geq 0$ relative to issuing a unit of debt. This cost may be driven by different factors, including forgone tax deductions on debt, debt overhang, agency costs, asymmetric information (see footnote [2]). In Appendix B, we show that the cost can be interpreted as the shadow cost of the capital constraint.

In total, if the dealer wins amount a_i at price p, the total (ex post) cost of adding $\kappa_i(pa_i)$ in capital is:

$$cost_i(a_i, p) = \kappa_i s(pa_i). \tag{3}$$

The total capital cost reduces the wealth (2) that is generated from purchasing the asset. Throughout the paper, we refer to $\kappa_i s$ as the "capital cost" (per-unit of the assets' value).

Once the auction clears, all transactions take place and banks do not have time to change their funding strategy.

Timing. Summarizing, the sequence of the game is as follows: First, each bank commits to a funding strategy. Second, each dealer i privately observes its inventory position z_i and bids in the auction, simultaneously with all other dealers. When the auction clears, all transactions take place and the game ends.

The sequential timing reflects the idea that the bank has to plan how to fund the oftentimes large auction purchase in advance. This implies that the bank will not hit

[11] This model feature relates to theories of optimal bank capital structure in which capital requirements are not necessarily binding (e.g., Flannery (1994); Myers and Rajan (1998); Diamond and Rajan (2000); Allen et al. (2011)).

the target level κ^* in all events, but only in expectation. Similarly, in the data, it looks as if banks target a capital ratio but may deviate from it. This target level is above the absolute minimum, which makes it possible to fall below it.

If instead we assumed that the funding and bidding decisions were made simultaneously and that each bank observed what its dealer knows at the time it bids, our main proposition would go through, but we could no longer derive an example equilibrium in closed form solution.

Equilibrium. 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)). This means that the equilibrium demand has the following functional form: $a_i(p) = \delta_i^0 + \delta_i^1 z_i - \delta_i^2 p$ with $\delta_i^0, \delta_i^1 \in \mathbb{R}$ and $\delta_i^2 > 0$. 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 (Uniform price auction)**.** *Let* $\mu_i = \mu - \rho\sigma z_i$ *and assume* $\mathbb{E}[\mu_i] \geq \frac{\rho\sigma A(N-1)}{N(N-2)}$*. There exists a unique equilibrium in which*

(i) dealer i *submits the demand curve*

$$a_i(p) = \left(\frac{N-2}{N-1}\right)\frac{1}{\rho\sigma}\Big(\mu_i - (1+\kappa s)p\Big) \text{ and} \tag{4}$$

(ii) each bank issues the fraction $\kappa = \frac{\kappa^*(1+c)-\kappa_0}{c-s(\kappa^*-\kappa_0)}$ *of the purchase as new capital with* $c = \frac{A}{N}(\mathbb{E}[\mu_i] - \frac{\rho\sigma A(N-1)}{N(N-2)})$.

To derive an intuition for statement (i), consider a dealer who picks how much to demand at a price p. The dealer takes κ_i and the behavior of other dealers as given and maximizes its expected utility from winning the asset when the market clears. The optimal demand equalizes the expected marginal utility (LHS) with the marginal payment (RHS):

$$\mu - \rho\sigma(z_i + a_i) = (1+\kappa_i s)(p + \Lambda_i a_i). \tag{5}$$

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 three components. The first is the per-unit price that the dealer pays to buy the asset. The second is the marginal cost, $\kappa_i ps$, from adding the necessary capital. Taken together, $(1 + \kappa_i s)p$ is the effective per-unit price the dealers pays. The last term, Λ_i, captures the price impact that a dealer's demand has on the market clearing price. It is known as "Kyle's lambda", and is zero if dealers are non-strategic, i.e., truthfully report their demands without shading bids.[12]

Statement (ii) characterizes how much new capital, κ_i, the bank issues relative to new debt, $(1 - \kappa_i)$. To do this, the bank takes an expectation over the asset's return, the dealer's inventory position at the time the dealer bids, and over where the market will clear. It then chooses κ_i so as to bring the capital ratio to the regulatory target level κ^*. This is achieved when

$$\kappa^* \text{Expected total assets} = \text{Expected total capital.} \tag{6}$$

In equilibrium all dealers and banks respond optimally to one another. The equilibrium exists and is unique if there is a set of κ_i's such that all banks play best responses. When all dealers are ex-ante identical, the unique equilibrium is symmetric, has a closed form solution and always exists.

Discriminatory pricing. 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.,

[12] See Kyle (1985, 1989); Malamud and Rostek (2017) for more details.

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.

We find and characterize an equilibrium under a functional form assumption: we impose that the amounts that bidders win in the auction follow a Generalized Pareto Distribution.[13] 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 2 (Discriminatory price auction)**.** *Let z_i be drawn from a bounded distribution with support $[\underline{z}, \overline{z}]$. Let the winning quantities $\boldsymbol{a_i^*}$ be drawn from a Generalized Pareto Distribution with CDF $F_{a_i^*}(a) = 1 - (\frac{\nu_i + \xi a}{\nu_i})^{-\frac{1}{\xi}}$ with scale parameter $\nu_i = -\xi(\frac{N(1-\xi)-1}{N(1-\xi)})(\overline{z} - z_i) - \xi(\frac{A}{N})$ and shape parameter $\xi \in (-\infty, -1]$. Define $\mu_i = \mu + \frac{\rho\sigma}{1-\xi}(\overline{z} - z_i) + \frac{\rho\sigma A}{N(1-\xi)-1}$ and let $\mathbb{E}[\mu_i] \geq \frac{\rho\sigma A(N-1)}{N(N(1-\xi)-1)}$.*

There exists a unique equilibrium in which

(i) dealer i submits the demand curve

$$a_i(p) = \left(\frac{N(1-\xi)-1}{N-1}\right)\frac{1}{\sigma\rho}\left(\mu_i - (1+\kappa s)p\right), \text{ and} \tag{7}$$

(ii) each bank issues the fraction $\kappa = \frac{\kappa^*(1+\bar{c})-\kappa_0}{\bar{c}-s(\kappa^*-\kappa_0)}$ of the purchase as new capital with $\bar{c} = \frac{A}{N}(\mathbb{E}[\mu_i] - \frac{\rho\sigma A(N-1)}{N(N(1-\xi)-1)})$.

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

[13]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.

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.

Model predictions. Having characterized an equilibrium under both auction formats, we can ask how the dealers' demands and market price change when capital ratios change or capital requirements are relaxed.

Corollary 1. *When the capital cost κs decreases, for instance, because κ^* decreases, or because s is set to zero,*

(i) demand becomes flatter,

(ii) market price increases, and

(iii) price manipulation, $m(\kappa s)$, defined as as the difference between the market price p_T^* that would arise if all banks were price-takers (i.e., truthful) and the market price p^* that arises when they are strategic, increases under both auction formats.

Consider first statements (i) and (ii). When the bank targets a lower capital ratio, κ^*, the bank issues less new capital (κ decreases) since it already holds sufficient capital to comply with the regulatory requirement. A lower κ, in turn, affects the demand curve and the market clearing price. The demand curve becomes flatter because the effective per-unit price, $(1 + \kappa s)p$, decreases. This is also the case when it becomes costless to hold capital ($s = 0$). As a result, the market clearing price increases in all cases.[14]

Statement (iii) highlights an implicit cost when relaxing capital requirements: banks distort the market price further away from the price that would arise if they

[14]A change in κ does not affect the price impact, Λ, which is the inverse of the slope of the residual supply curve that bank i considers when submitting its demand: $\Lambda = (\frac{\partial RS_i(\tilde{p})}{\partial \tilde{p}})^{-1}$, where $RS_i(\tilde{p}) = A - \sum_{j \neq i} a_j(\tilde{p})$ with $\tilde{p} = (1 + \kappa s)p$. While the effective per-unit price $\tilde{p}$ increases, the slope of the residual demand curve, and thus Λ, remains unchanged.

were price-takers. This is a source of market inefficiency as the distorted price can affect the final security allocation.

Formally, in the uniform price auction, $m(\kappa s) = p_T^* - p^*$ is the average amount a bidder shades at market clearance:

$$m(\kappa s) = \frac{\rho\sigma}{(1+\kappa s)}\left(\frac{A}{N}\right)\left(\frac{1}{N-2}\right) = \frac{1}{N}\sum_i shading(a_i^*), \tag{8}$$

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.

Manipulation decreases in κs because each bank cares about the effective price $(1+\kappa s)p$ it pays, not the actual price p. At market clearing the bank shades the effective price by the same amount that the bank would shade p if the actual price was the effective price ($\kappa s = 0$): $shading(a)(1+\kappa s) = \rho\sigma\left(\frac{a}{N-2}\right)$. As a result, shading per actual price, $shading(a)$, and thus manipulation, decreases in κs.

This is also true in the discriminatory price auction, where $m(\kappa s) = p_T^* - p^*$ takes a similar expression:

$$m(\kappa s) = \frac{\rho\sigma}{(1+\kappa s)}\left(\frac{A}{N}\right)\left(\frac{\xi}{\xi-1}\right). \tag{9}$$

However, given that bidders pay the prices that they bid instead of the market clearing price, $m(\kappa s)$, differs from the average shading amount:

$$\frac{1}{N}\sum_i shading(a_i^*) = \frac{\rho\sigma}{(1+\kappa s)}\left(\frac{\xi}{\xi-1}\right)\left(\overline{z} - \frac{1}{N}\sum_i z_i\right). \tag{10}$$

The main insight is that under both auction formats the market price and the degree of price manipulation change one-to-one when the capital cost changes. Corollary 2 formalizes this result.

Corollary 2. *Define* $\eta_p = \frac{\partial p^*(\kappa s)}{\partial \kappa s}\frac{\kappa s}{p^*(\kappa s)}$ *and* $\eta_m = \frac{\partial m(\kappa s)}{\partial \kappa s}\frac{\kappa s}{m(\kappa s)}$ *as the capital cost elasticity of the market price and the capital cost elasticity of price manipulation, respectively. The former tells us by how much the market price changes (in %) when the marginal capital cost* κs *increases by 1%. The latter quantifies by how much price manipulation changes (in %) when the marginal capital cost increases by 1%.*

Under both auction formats,

$$\eta_p = \eta_m = \frac{1}{1+\kappa s} - 1. \tag{11}$$

Take away. Our model illustrates how capitalization and capital requirements affect asset demand of dealers, and ultimately asset prices. In particular, Corollary 1 makes predictions about what happens when banks face lower capital costs. These predictions hold in all settings that we consider, including our modified model of He and Krishnamurthy (2012, 2013) presented in Appendix B.

3 Institutional setting and data

To test the predictions of Corollary 1 (hereafter referred to as hypothesis) and to quantify the capital cost elasticities of Corollary 2, we use data on Canadian Treasury auctions, i.e., the primary market for Canadian government bonds. 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.[15] They dominate the Canadian government bond market. They intermediate the vast majority of the daily trade volume with government bonds. Each dealer is part of a large bank, for instance, Royal Bank of Canada Dominion Securities is part of Royal Bank of Canada. 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. This is a small part of the bank's total business, which includes accepting

[15]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.

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 bank level.

As in our model, we refer to the primary dealer as dealer and the company holding level as bank to highlight that capital requirements are fulfilled at the bank level. However, we use the same subscript i to emphasize that the dealer is part of the bank.

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. In theory, anyone may participate. In practice, 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.[16]

Capital indicators. According to a recent survey among market participants, the Basel III Leverage Ratio represents the most relevant capital constraint when trading government bonds (see CGFS (2016)). This regulatory requirement came into effect in September 2014 as a complement to risk-weighted capital ratios. It puts a restriction on the balance sheet of an institution, and was criticized for imposing a high cost (see Duffie (2018)). Formally, the LR measures a bank's Tier 1 capital relative to its total leverage exposure, and must be at least 3%:

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

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

[16]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.

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.

While the minimum LR must be at least 3%, banks refrain from getting close to this constraint (see Figure 2, explained below). One reason is that the regulator also prescribes authorized requirements for individual institutions.[17] These supervisory LR thresholds are communicated to individual institutions on a bilateral basis. They are considered supervisory information and are not permitted to be disclosed to the public. Another reason is that banks are required to hold a sufficient conservation buffer for Tier 1 capital. If they don't, they are punished in that distributions (including dividends and share buybacks, discretionary payments and bonus payments to staff) are restricted.

The regulation changed during the COVID-19 crisis. When dealers failed to absorb the extraordinary supply of government bonds in March 2020, government bonds, central bank reserves, and sovereign-issued securities that qualify as High Quality Liquid Assets (HQLA) were temporarily exempted from the LR on April 9, 2020, thereby making it cheaper for dealers to hold these assets on their balance sheets (Duffie (2020); He et al. (2022); Schrimpf et al. (2020)).[18] The exemption of government bonds and HQLA ended on December 31, 2021, while reserves continued to be excluded.[19] Our empirical strategy leverages these policy changes.

Data sources. 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

[17]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.

[18]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.aspx`, accessed on 05/31/2022.

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

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.

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.[20]

We augment this main data with two additional sources. First, 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. Second, we download the CBOE Volatility Index (VIX), which measuers the market's risk-neutral expectations for volatility over the coming 30 days, from Bloomberg.

Slope measures. Our model predicts that demand curves become flatter as banks are less capitalized or capital requirements are relaxed, which affects the asset's price via market clearing. To provide evidence for this mechanism, we need to measure by how much the slope of each dealer's demand changes when capital costs change. The slope measure should be dealer and auction-specific so as to account for differences in capitalization, capital requirements and market conditions. Creating such a measure, however, is challenging. For instance, we cannot simply regress demand on prices 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, we rely on our model which stylizes how Canadian Treasury auctions work in reality. To bridge the gap between theory and empirics,

[20]For a detailed description of the key variables of LR, see Appendix D. 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.

Figure 1: Example of a demand function with 6 steps

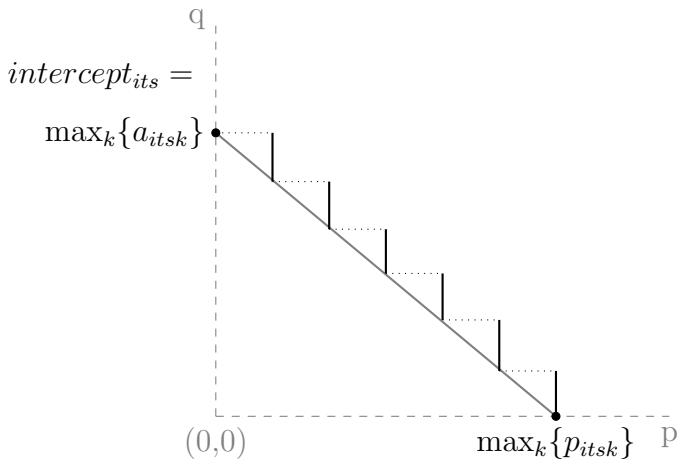


Figure 1 illustrates how we measure the slope of demand of dealer i on day t for security s. In black, we show an example of a step-function, $\{a_{itsk}, p_{itsk}\}_{k=1}^{6}$, that a bidder could submit at auction (with prices instead of yields). In gray, we show a continuous, linear demand function, $q(\cdot)$, 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.

assume for a moment that in the auction dealers can submit linear demand curves that map from prices to quantities, like in the model (Proposition 2). 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,

$$slope_{its} = \frac{\max_k\{a_{itsk}\}}{\max_k\{p_{itsk}\}} \text{ for } K_{its} > 1, \tag{12}$$

is an approximation (see Figure 1). Second, the value of the bond is expressed in yields (the annualized interest rates that equates the prices with the present discount values of the bonds) rather than prices. This means that the submitted demand curves are upward sloping. To incorporate this difference in the measurement, we convert the maximal price in equation (12) into the corresponding yield for our empirical exercises.

One concern with slope measure (12) 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, defined in Appendix D.[21] Among all slope measures, measure (12) 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.[22]

Summary statistics and conventions. When we display demand graphically, we show quantities on the y-axis and prices or yields on the x-axis (as in Figure 1), different from the text-book convention. That way, the plotted function becomes flatter when our model predicts a flatter demand curve, $q(\cdot)$. If we flipped the y- and x-axis around, the graphs would show steeper curves when the hypothesis predicts flatter demand, which we find confusing.

[21] 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.

[22] 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.

Table 2: 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
Slope of demand (in $\frac{\text{bn C\$}}{\%}$)	2.02	0.80	3.68	0.01	57.14
Amount dealer won (in mil C$)	277	150	395	0	5,739
Quarterly LR (in %)	4.41	4.36	0.28	-	-

Table 2 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.

All quantities are measured in billion C$, prices in C$ and ratios, as well as yields in %, unless stated otherwise. Our slope measure is expressed in billion C$ per percentage point (i.e., 100 bps), since it is the ratio between demand (in billion C$) and yields (in %). An overview of the main variables is presented in Table 2.

4 Demand and yield effect

Demand effect. To provide evidence that demand curves become flatter when capital requirements are relaxed and steeper when they are tightened, we leverage the fact that government bonds were exempted from the LR from April 2020 until the end of December 2021 to buffer the negative effects of the liquidity crisis triggered by the COVID-19 pandemic (see Figure 2).[23] This means that, in the exemption

[23]An alternative approach to gather evidence could be to look at how the slope of demand curves changes around the policy changes. Doing so, however, it is difficult to separate by how much the slope changes due to capital costs versus other, partially unobservable factors that affect the slope and fluctuate over time. Examples include the bank's risk bearing

Figure 2: Time series of LR for an average bank

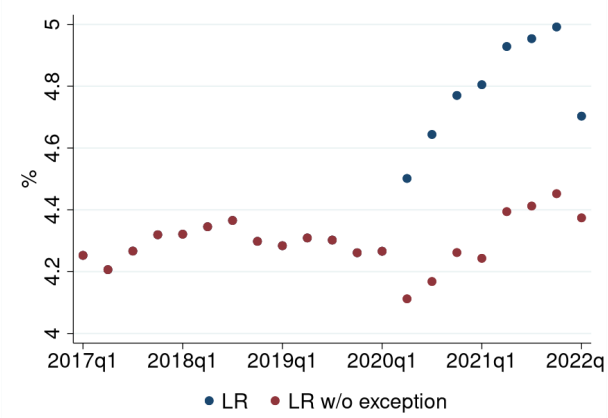


Figure 2 shows the time series of the LR (in %) of an average bank. In blue, we show the actual LR. In red the counterfactual LR that the average bank would have had if central bank reserves and sovereign-issued securities that qualify as high quality liquid assets and exposures related to the US Government Payment Protection Program (PPP) were not exempt. Prior to the policy intervention in 2020q2, these two LR coincide and are a consistently at roughly 4.3%. After that, the actual LR increases significantly, moving it away from the regulatory minimum. The LR drops back down when government bonds are no longer exempted in 2022q1. It does not get back to its original level, partially because central bank reserves are still exempted.

period, dealers could buy government bonds without having to increase their capital holdings. Through the lenses of our model, the capital cost, s, was set to zero.

We test by how much changing the capital requirements affected the demand slopes via a dynamic Difference-in-Difference regression. For this, we collapse the data on the dealer-quarter level and estimate the following regression:

$$slope_{iqs} = \alpha + \sum_{k=-K}^{K} \gamma_k * D_k * capital_requirement_{ik} + \zeta_{qs} + \epsilon_{iqs}, \tag{13}$$

where $slope_{iqs}$ is the average slope in the demand function of dealer i in quarter q for security s and D_k is an indicator variable that assumes value 1 k quarters before/after the event quarter, 2020q2, $capital_requirement_{ik}$ is either the dealer's LR in quarter k or the dealer's supervisory LR threshold, and ζ_{qs} are quarter-security fixed effects.

capacity, which likely depends on its portfolio holdings, and dealer beliefs when competing in the auction, which are captured by ρ and ξ in Proposition 2, respectively. Therefore, we refrain from such an analysis.

Figure 3: Change in the slope

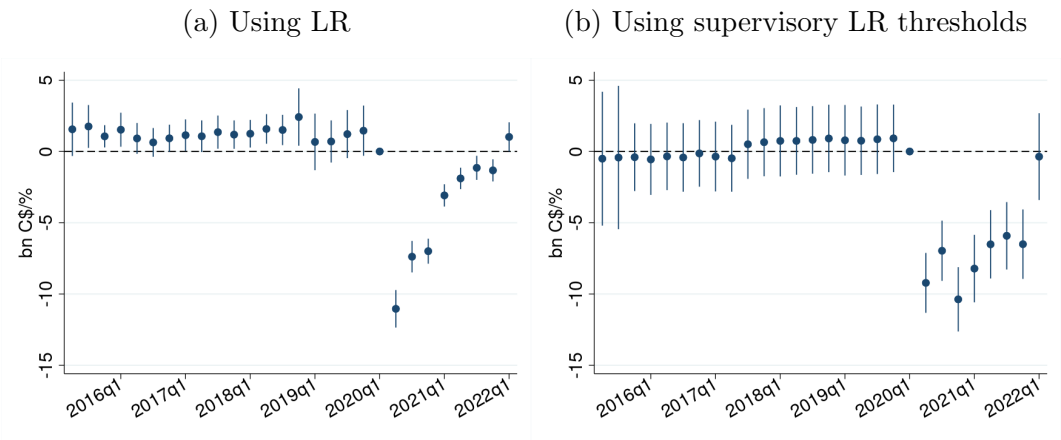


Figure 3a shows the γ_k estimates and 95% confidence intervals of the regression (13): $slope_{iqs} = \alpha + \sum_{k=-K}^{K} \gamma_k * D_k * LR_{ik} + \zeta_{qs} + \epsilon_{iqs}$. Figure 3b replaces LR_{ik} by the institution-specific Basel III threshold. All magnitudes are relative to the benchmark in 2020q1. The slopes are measured in billion C$/percent.

In Figure 3a, we first use the LR_{iq} as independent variables to directly exploit the variation in these ratios that was triggered by the temporary exemption of government bonds. The parameters of interest, γ_0 and γ_7, tells us by how much the slope changes given a change in the LR—first relaxing it, then tightening it. All γ parameters are identified from the variation in LR_{iq} across banks within a quarter.

One concern is that the leverage ratio is not fully exogenous to the dealer. Even though the dealer only controls a small part of the holding company's balance sheet and has generally different objectives, it may change bidding behavior in the beginning of a quarter so as to affect the bank's leverage ratio. Such manipulation is much harder, if not impossible, for the supervisory LR thresholds. These thresholds are set by the regulator at the level of the holding company and do not vary when the balance sheet changes.

Therefore, we use the supervisory LR thresholds in a second and preferred specification (see Figure 3b). Now, 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.

In line with our hypothesis, we find a sharp drop in the slope. After 2020q2, the slope recovered back up during the rest of the exemption period when using the LR ratios, but not in our preferred specification.[24] In both cases, the slope jumps upwards when government bonds are no longer exempt.

The slope changes triggered by a one percentage point increase in LR are sizable (C$10 billion/percent) in comparison to the average slope of all banks and all periods (C$2.02 billion/percent).[25] Assuming that supply adjusts in a way that the market clears at the same yield and all dealers win the same amount as before, even though they are now submitting flatter demand curves, the slope change implies that the demand elasticity decreases by at least 5% in response to a 1% LR increase (assuming 4.3% is base line).[26]

The estimated relationship is causal if the exemption and inclusion of government bonds for LR purposes were exogenous events. This means that the Canadian regulator did not choose to change the LR requirement in response to how dealers bid in the primary auctions. We believe that this is unlikely given that Canada was part of a global response to increase operational capacity of banks in light of global market conditions (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 policy-driven, exogenous change in LR—anything that affected the slopes of different dealers in the same way is absorbed by the quarter-security

[24]One reason for the upward trend in the slope when using LR ratios is that those dealers who were most positively impacted by the LR exemptions demanded larger amounts than in 2020q2 in subsequent quarters (see Appendix Figure A2). This mechanically increases the slope measure.

[25]This means that on average a bank demands C$20.2 million less when the yield decreases by 1 bps. In 2020, for example, when the LR exemption increased the average LR by 0.2%, the demand decreased by roughly C$0.2 (=20.2-0.2*10,000/100) million given a yield increase of 1 bps, assuming, for illustration, that C$2.02 billion/percent is the correct benchmark.

[26]We define the average demand elasticity as slope * average yield/average amount a dealer wins. Using the averages reported in Table 2, the average demand elasticity is C$2.02 billion/% * 0.92%/C$277million = 6.709. Given a 1% increase of LR, the elasticity change is C$(10/100) billion/%*0.92%/C$277million=0.33. This is roughly 5% of the average elasticity. Since this average elasticity includes the period with the LR exemption, in which the elasticity was lower, the actual change must be larger than 5%.

fixed effect.

Two concrete confounding factors come to mind. Both are policy interventions that aimed at re-establishing market liquidity after the dash-for-cash in March 2020 when investors sold government bonds in exchange for cash. First, the Bank of Canada increased the maximal bidding limits in April 2020 so as to allow dealers to buy larger amounts of government bonds. The policy ended in June 2021, thus cannot have affected the upward jump in the slope when the LR was tightened. Further, it rarely had an effect since pre-COVID maximal bidding limits were typically not binding (see Appendix Figure A3). Second, the Bank of Canada started buying government bonds in the secondary market via quantitative easing in April 2020 until October 2021.

Both policy interventions were meant to help ensure that dealers continued to buy sufficiently in the primary market.[27] 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 (12). Instead, controlling for unobservable that affected all dealers homogeneously (which could include these policy interventions), we find that the slope drops. We therefore don't think that the change in bidding limits or quantitative easing drives our findings. Moreover, neither of the two confounding factors were present in January 2022, but we still see a significant effect (especially in Figure 3b).

We conduct a series of robustness checks. First, in Appendix Figure A1, we add dealer fixed effects to take out time-invariant unobservable dealer characteristics, but warn that this regression could be over-specified. Second, 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 A5). 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. Third, we exclude dealers

[27]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 A3).

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 A4).

Yield effect. When demand becomes flatter the market clearing price must increase, 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 price 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 price. We can no longer rely on variation of capital or leverage ratios across dealers. However, we can compare market prices across time, and control for unobservable factors that moved prices 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, decreasing the marginal cost of adding new capital to fulfill capital requirements, 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, $benchmark_yield_t$.[28] 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 3). To get a sense of the size of the

[28]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.

Table 3: 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 3 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). * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

effect, recall that the leverage ratio increased from an average of 4.3% to 4.5%. 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.

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 face lower capital costs. This decreases the market yield. To quantify these effects and avoid endogeneity issues, we take our model to the data in the final part of the paper.

5 Capital cost elasticities and counterfactuals

Our goal is to quantify the capital cost elasticity of the market price and of price manipulation, defined in Corollary 2. With these elasticities, we conduct counterfactuals to analyze what would have happened to prices and the degree of price manipulation had the Canadian regulator not changed the capital requirement for government bonds during the COVID-19 pandemic.

5.1 Calibration

The key parameter of interest is the marginal cost of capital. The idea is to identify this parameter from how much price manipulation changes when the LR constrained is relaxed. Recall that shading at market clearing (10) depends on the bank's risk aversion and inventory positions, the distribution of the winning quantities, market volatility, and the marginal capital cost. If we are willing to assume that the change in LR did not directly affect the bank's risk aversion, we can identify the marginal capital cost from how much price manipulation changes when the policy changes, conditional on inventory positions, market volatility and distribution of winning quantities.

Stage 1. Our estimation procedure has two steps. First, we estimate by how much banks shade their bids and the distribution of winning quantities in each auction. This can be done with prices in C$ as in our model or with prices expressed as yield to maturity in bps as in our empirical section, equivalently.

We rely on techniques that were developed by Guerre et al. (2000), Hortaçsu and McAdams (2010) and Kastl (2011) to back out bidder's true willingness to pay in multi-unit auctions to account for the fact that, in practice, bidding in the auctions is more complicated than in any tractable theory model.[29] There are two bidder groups, dealers and customers, who may differ from one another. Each bidder submits step functions rather than continuous functions and may condition their bids on different information sets. Hortaçsu and Kastl (2012) characterize first-order equilibrium conditions for a game with these features.

[29]For an overview of this literature see Kastl (2020) or Clark et al. (2021).

Similar to the equilibrium demand in Proposition 2, the equilibrium condition depends on the distribution of the amount that a bidder wins in auction t, $F_{ti}(\cdot)$. We estimate this distribution using resampling methods. If only dealers participated in the auction, we would fix a bidder i in the auction, and draw N times from the pool of submitted bids with replacement. We would let the auction clear and compute the market clearing price p_t^* and how much this bidder would have won a_{it}^* in the auction. We would repeat this many times and for all bidders to obtain the distribution of a_{it}^* for all i. In practice, because there are two bidder groups, we follow the more complicated resampling procedure by Hortaçsu and Kastl (2012).

With the distribution of winning quantities, we can back out the willingness to pay that rationalizes the bids that we observe in an auction, assuming that all bidders play a Bayesian Nash equilibrium (see Hortaçsu and Kastl (2012)). The difference between the submitted bid and the estimated willingness to pay of bidder i in auction t at the market clearing price measures the shading factor, $\hat{s}hading_{it}(a_{it}^*)$.

Stage 2. Second, we compare the amount of shading in the auction right before a policy change of the LR with shading in the auction right after the two policy changes (on April 9, 2020 and January 1, 2022). The change in shading pins down the marginal cost of capital, if, within the short time window around the policy change, the banks' risk aversion remained constant. The level in shading pins down the degree of risk aversion.

Alternatively, we could average across shading of all auctions within a quarter and compare the average shading in the last quarter before each of the policy changes with the average shading in the first quarter after the change. This approach would be closer to the Difference-In-Difference analysis presented above, which we motivated by the fact that the LR must be reported quarterly. However, this approach would require assuming that the banks' risk aversion remained constant over a longer horizon. This might be a strong assumption given that a bank's risk aversion likely depends on the bank's ability to diversity risk based on its portfolio holdings and market conditions that vary over time. We therefore prefer to compare shading in the auctions around the policy change.

We restrict our sample to the eight deposit taking banks which were affected by the policy change, and assume that expression (10) approximates their shading at market clearing to a first-order degree. We fit the empirical distribution of winning quantities, $\hat{F}_{ti}(\cdot)$, to the match the Generalized Pareto distribution of Proposition 2 with shape parameters $\hat{\xi}_t \in \mathbb{R}$.[30] With this, we back out the marginal cost of capital by comparing how much banks shade before and after the policy change.

For illustration, consider the first policy change on April 9, 2020. In the last auction on April 8, 2020 before the change ($t = 1$):

$$\frac{1}{N}\sum_i \hat{s}hading_{i1}(a^*_{i1}) = \frac{\sigma_1\rho}{(1+\kappa s)}\left(\frac{\hat{\xi}_1}{\hat{\xi}_1 - 1}\right)\left(\overline{z}_1 - \frac{1}{N}\sum_i z_{i1}\right)$$

and in the first auction after the change on April 14, 2020 ($t = 2$):

$$\frac{1}{N}\sum_i \hat{s}hading_{i2}(a^*_{i2}) = \sigma_2\rho\left(\frac{\hat{\xi}_2}{\hat{\xi}_2 - 1}\right)\left(\overline{z}_2 - \frac{1}{N}\sum_i z_{i2}\right).$$

Dividing the first expression by the second cancels out ρ and gives us κs, given that we know all other elements of these expressions other than ρ. We have estimated the shading factors and the $\hat{\xi}$'s, and observe the ratio of market volatility $\frac{\sigma_1}{\sigma_2} = \frac{45.9}{40.24}$ from the volatility indices (VIX) on those dates. We also observe the inventory positions of all bidders z_{it} and use the largest inventory position that we observe in any auction of the same maturity-length as those around the policy change in our sample as an upper bound of the support of its distribution, $\overline{z}_1 = C\$3,725$ million and $\overline{z}_2 = C\$2,136$ million. Similarly, we can use the second policy change on January 1, 2022, reverting back to the original LR requirements. Here, we compare shading on the last auction day in 2021 (December 21) with shading on the first auction day in 2022 (January 5), using $\frac{\sigma_1}{\sigma_2} = \frac{22.28}{17.07}$ and $\overline{z}_1 = C\$2,136$ million and $\overline{z}_2 = C\$2,136$ million as input

[30] In contrast to Proposition 2, we now allow ξ_t to be larger than -1. This restriction guarantees that an equilibrium always exists and is more stringent than strictly necessary. As comparison, Ausubel et al. (2014) only require $\xi < \frac{N-1}{N}$ which ensures that demand curves are downward sloping. Further, the empirical literature typically does not impose that sufficient conditions must be met, the idea being that there is an equilibrium if we observe such behavior in the data. We follow this approach.

Table 4: Estimated parameters

Relax LR:	$\hat{m}(\kappa_1 s_1)$	$\hat{m}(0)$	$\hat{\xi}_1$	$\hat{\xi}_2$	$\hat{\rho}$	$\hat{\kappa s}$	$\hat{\eta}$
	0.656 bps	0.614 bps	-1.527	-1.081	$\frac{1.42}{10^5}$	0.906	-0.475
Tighten LR:	$\hat{m}(0)$	$\hat{m}(\kappa s)$	$\hat{\xi}_1$	$\hat{\xi}_2$	$\hat{\rho}$	$\hat{\kappa s}$	$\hat{\eta}$
	2.011 bps	0.655 bps	-1.188	-1.089	$\frac{7.61}{10^5}$	1.224	-0.550

Table 4 shows the calibrated parameters of our model, around both policy changes, when LR was relaxed, on April 9 2020 and, when LR was tightened, on January 1 2022. The first and second column show the yield manipulation (in bps) before the policy change ($t = 1$) and after ($t = 2$). The third and forth column show the estimated shape parameter of the distribution of winning quantities in each auction. The fifth column shows the degree of risk aversion, The sixth column shows the marginal capital cost and the last column shows the cost elasticity, defined in (11).

variables.

With κs, we can back out the bank's risk aversion around both policy changes, $\hat{\rho}$ from the level of either of the two shading equations.

5.2 Estimation findings

As in our empirical section, we measure bids and shading in yields to maturity, measured in bps. An overview of the estimated parameters is in Table 4.

Yield manipulation. In line with the existing literature, we estimate shading factors of 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.

Shading is driven by where the bidder expects the market to clear, i.e., her (Generalized Pareto) distribution of the winning quantities. The shape parameter ξ of this distribution varies relatively little across auctions and it close to -1. This means that the bidder believes to win all quantities for which it bids with roughly similar probability.

Risk aversion and capital cost. We find that banks are close to risk neutral with both risk aversion coefficients being very close to zero. This is in line with our

expectation given that these are the largest banks in Canada who have the ability to diversity away most types of risk.

In contrast, the marginal capital cost κs is sizable with 0.906 in 2020 and 1.224 in 2022. If the average bank targets a capital ratio of roughly 4.3%, this implies a shadow cost (or Lagrange multiplier) of $s = 0.906/0.043 = 21$ in 2020 and $s = 1.224/0.043 = 28$ in 2022. To get a sense of the magnitude, recall that to meet the regulation target, the bank has to add κpa of capital when it buys pa worth of Treasuries. This costs $cost(pa) = \kappa spa$. Thus, $\frac{\partial cost(pa)}{\partial pa} = \kappa s = 0.906$ means that for each unit worth of Treasuries the bank buys, it takes into account that it must increase its capital and that this will cost only a bit less than what the added Treasury is worth. In 2022, the cost of increasing capital to match the increase in Treasuries out-weights the value of the added Treasury, today. Banks still buy Treasuries because they expect to get a positive return in the future, despite high capital costs today.

Comparing the risk aversion and capital cost estimates of 2020 with those from 2021, we see that banks became slightly more risk averse and capital costs increased. On first glance, this is counterintuitive given that the LR is further above the minimal threshold (recall Figure 2), suggesting that banks are less capital constrained. However, one reason for why the LR remains high in early 2022 is the treatment of settlement balances. Although these remained excluded, the exemption is temporary. Banks have to take into account that at some point in the future the exemption will be lifted, which 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. As primary dealers, the banks have an obligation to buy these bonds, which can increase their exposure and lower the LR.

Cost elasticity. The capital cost elasticity of the market price and of price manipulation, defined in Corollary 2, range between -0.475 and -0.550. This means that the market yield increases by 0.47%–0.55% if the marginal capital cost increases by 1%. For instance, the average yield of 193 bps would increase by 0.47%–0.55% * 193 bps = 0.9-1.0 bps.

In comparison, the reduced-form evidence says that a one percentage point in-

crease of the LR—which moves the bank further away from the minimal capital threshold and thus decreases capital costs—increases the yield by roughly 25–36 bps in absolute terms. In relative terms, this roughly says that a (1/4.3) =23% increase in LR increases the yield by 25/193–36/193=12%–18%. This implies that a 1% increase in LR increases the yield by roughly 12/23%–18/23% = 0.57%–0.78%. These numbers are similar to our calibrated estimates.

This comparison provides some 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 downward biased because of endogeneity.

Counterfactual. With the model we can quantify by how much the auction yield and yield manipulation would have changed had the regulator not changed the LR requirement.

For illustration, consider the first auction after the LR was relaxed. This auction cleared at a yield of 43.6 bps with 0.61 bps of yield manipulation. Instead, had the LR not been relaxed, which corresponds to a cost increase of 100%, the auction yield would have increased by roughly 47% to 64 bps. This translates into a reduction in auction revenue. At the same time, yield manipulation would also have decreased by 47% to 0.32 bps. In contrast, the first auction after the LR was tightened cleared at 56.2 bps, with a manipulation of 0.65 bps. Had LR not been relaxed, the auction would have cleared at 25 bps with yield manipulation of 1 bps.

Given the low yields throughout our sample, these numbers are small in absolute terms. However, these calculations highlight that the change in LR had a sizable impact on auction outcomes in relative terms. Not only did the policy change affect the market price, it also non-negligibly affected the degree of price manipulation. 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.

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 the degree of price manipulation.

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A Appendix

B Alternative Model

Here, we present an alternative framework that makes the same predictions as our main model. The key difference is that dealer-banks now face capital constraints which may or may not bind. They no longer target to hold a specific capital ratio.

The model shares some similarities to the intermediary sector in He and Krishnamurthy (2013, 2012). There are two main differences. First, we focus on frictions that arise from regulatory capital constraints rather than moral hazard. Second, the market for the risky asset is not perfectly competitive. Instead, intermediaries are strategic players who have price impact and internalize that they do in the spirit of Kyle (1989).

Players and preferences. The game has two periods ($t = 0, 1, 2$). There is a risky asset of total supply A that pays a return $R \sim N(\mu, \sigma)$ per share in period 2 and a riskless asset which serves as numerair.

In the model presented in the main text, each dealer has private information about its inventory position. Here, we abstract from private information and let the noise come from aggregate uncertainty about the total supply of the asset: A is drawn from an arbitrary but commonly known distribution. This is mathematically simpler and allows us to focus on the main point. In reality, A represents the amount that is issued to dealers who bid competitively, rather noncompetitive bidders in a primary auction, or the amount that will be actively traded in a day on an exchange. Both are unknown to the dealers before market clearance.

$N > 2$ dealers purchase the risky asset. They obtain CARA utility from the wealth w_i they hold in period 2:

$$\pi_i(w_i) = 1 - \exp(-\rho w_i) \text{ with risk-aversion } \rho > 0.$$

Sequence of events. In period 0, each dealer holds the same equity capital $E > 0$ and makes some commercial loans of amount x to an un-modeled corporate sector.

Dealers compete to buy the risky asset in a uniform price auction, as described in the main text.

The dealer's objective is to maximize the utility that it expects to earn from the wealth that the auction purchase generates in period 2:

$$w_i = a_i^* R - p^* a_i^* + E. \tag{14}$$

It faces a capital constraint in the spirit of the Basel III capital requirement (without risk adjustment):

$$k \leq \frac{E}{p^* a_i^* + x} = \frac{\text{total capital}}{\text{total exposure}} \tag{15}$$

where k denotes the capital charge on the risky asset and on the loan. It is independent of asset characteristics.

Proposition 3. *Let* $\mu - \frac{A}{N}\left(\frac{N-1}{N-2}\right)\rho\sigma > 0$. *There exists a unique equilibrium in which each dealer submits a demand curve*

$$a_i(p) = \left(\frac{N-2}{N-1}\right)\frac{1}{\rho\sigma}\Big(\mu - (1+\lambda k)p\Big), \tag{16}$$

where

$$\lambda = \begin{cases} -\frac{1}{k} + \frac{A}{N}\left(\frac{1}{E-kx}\right)\left(\mu - \frac{A}{N}\left(\frac{N-1}{N-2}\right)\rho\sigma\right) > 0 & \text{if } kp^*A/N + kx = E \\ 0 & \text{if } kp^*A/N + kx < E \end{cases} \tag{17}$$

with market clearing price $p^* = \frac{1}{1+\lambda k}\left(\mu - \rho\sigma\left(\frac{N-1}{N-2}\right)\frac{1}{N}A\right)$.

Having characterized the equilibrium, we are interested in how demand and prices behave if the capital stock changes or capital requirements change. To make the analysis interesting, we assume that the capital constraint is binding, i.e., $\lambda > 0$.

To assess effects from a shock to capital, we let there be an exogenous capital shock in period 0 that reduces E. We consider two scenarios. In the first, dealer's have constant absolute risk aversion. In the second, the dealer adjusts its preferences in a way to keep relative risk aversion constant. With CARA utility, relative risk

aversion γ_i is determined by the absolute risk aversion ρ and wealth: $\gamma_i = \rho w_i$. This implies an increase in $\rho = \gamma_i / w_i$. Formally $\frac{\partial \rho}{\partial E} = -\gamma_i w_i^2 \frac{\partial w_i}{\partial E} = -\gamma_i w_i^2$ given (14).

Corollary 3. *Demand becomes flatter and the market price, as well as price manipulation increase when*

1. *capital increases (E increases) and dealers have constant absolute risk aversion,*
2. *capital decreases (E decreases) and dealers have relative absolute risk aversion and are sufficiently risk averse (γ_i is high),*
3. *capital requirement is relaxed (κ decreases).*

The Corollary highlights that the effect of a change in capital depends on the type of risk aversion that dealers face. If dealers become more risk averse when they are hit by a negative capital shock, demand becomes flatter and the market price increases. This would be in line with ideas in intermediary asset pricing models of He and Krishnamurthy (2013, 2012) and Brunnermeier and Sannikov (2014). In these models, when the dealer experiences a negative shock to its capital the risk bearing capacity is impaired. This translates into an increase in risk aversion in our setting. If instead, the dealer's risk aversion is independent of how much capital they hold, the effect goes in the opposite direction.

C Proofs

C.1 Proof of Proposition 1

Consider a dealer and its bank, and assume that other dealer-bank pairs play according to the equilibrium strategy.

Recall that the dealer bids in the auction, while the bank determines how to finance this purchase in parallel or before the auction. The dealer guesses the funding strategy of its bank and chooses the best reply given the behavior of its competitors. The bank, in turn, guesses how the auction will clear, anticipating how its dealer will bid. In equilibrium, the guesses of all dealers and banks must be correct, given everyone behaves optimally.

Dealer demand. When choosing its optimal demand, the dealer takes fraction κ_i, and the bidding behavior of the other dealers as given. It determines its best reply by optimizing point-wise. For a fixed amount a_i, the dealer maximizes

$$\pi_i(p) = \mathbb{E}\left[1 - \exp\Big(- \rho[(z_i + a_i)R - (1 + \kappa_i s)pa_i - \psi z_i]\Big)\right]$$

with respect to p, subject to market clearance: $RS_i(p) = a_i$, where $RS_i(p) = A - \sum_{j\neq i} a_j(p)$ denotes bank i's residual supply. Given $R \sim N(\mu, \sigma)$,

$$\pi_i(p) = \mu(RS_i(p) + z_i) - \sigma\rho\frac{(RS_i(p) + z_i)^2}{2} - (1 + \kappa_i s)pRS_i(p) - \psi z_i.$$

The first order condition (FOC) is

$$0 = \mu RS_i'(p) - \sigma\rho(RS_i(p) + z_i)RS_i'(p) - (1 + \kappa_i s)pRS_i'(p) - (1 + \kappa_i s)RS_i(p).$$

The second order condition is satisfied since $RS_i(p)$ is a linear function given that all banks other than i submit demand curves as in (**??**) and $RS_i'(p) > 0, \sigma, \rho > 0, (1 + \kappa_i s) \geq 0$. To characterize the best reply, we rearrange the FOC. Label $1/RS_i'(p) = \tilde{\Lambda}_i$, and use that by market clearing $RS_i(p) = a_i$.

$$0 = \mu\frac{1}{\tilde{\Lambda}_i} - \sigma\rho(z_i + a_i)\frac{1}{\tilde{\Lambda}_i} - (1 + \kappa_i s)p\frac{1}{\tilde{\Lambda}_i} - (1 + \kappa_i s)a_i$$

Multiply by $\tilde{\Lambda}_i$ and rearrange.

$$\begin{aligned}
0 &= \mu - \sigma\rho(z_i + a_i) - (1 + \kappa_i s)p - (1 + \kappa_i s)a_i\tilde{\Lambda}_i \\
\mu - \sigma\rho(a_i + z_i) &= (1 + \kappa_i s)p + (1 + \kappa_i s)\tilde{\Lambda}_i a_i \\
a_i(p) &= ((1 + \kappa_i s)\tilde{\Lambda}_i + \sigma\rho)^{-1}(\mu - \sigma\rho z_i - (1 + \kappa_i s)p) \qquad (18)
\end{aligned}$$

In equilibrium, all banks submit best replies to each other. Therefore, $\tilde{\Lambda}_i$ is

$$\tilde{\Lambda}_i = \frac{1}{RS_i'(p)} = \left(\sum_{j\neq i}((1 + \kappa_i s)\tilde{\Lambda}_j + \sigma\rho_j)^{-1}(1 + \kappa_i s)\right)^{-1}$$

given $RS_j(p) = A - \sum_{j \neq i} a_j(p) = A - ((1+\kappa_i s)\tilde{\Lambda}_j + \sigma\rho_j)^{-1}(\mu - \sigma\rho_j z_j - (1+\kappa_i s)p)$.

$$\tilde{\Lambda}_i = \frac{1}{RS_i'(p)} = \left(\sum_{j \neq i} (\tilde{\Lambda}_j + \frac{\sigma\rho_j}{1+\kappa_j s})^{-1} \right)^{-1}$$

By Malamud and Rostek (2017) Proposition 1,

$$\tilde{\Lambda}_i = \tilde{\beta}_i \alpha_i \sigma \text{ with } \tilde{\beta}_i = \frac{2}{\alpha_i \tilde{b} - 2 + \sqrt{(\alpha_i \tilde{b})^2 + 4}} \text{ and } \alpha_i = \frac{\rho}{1+\kappa_i s},$$

where $\tilde{b} \in \mathbb{R}^+$ is the unique positive solution to $1/2 = \sum_i (\alpha_i \tilde{b} + 2 + \sqrt{(a_i \tilde{b})^2 + 4)^{-1}}$. Equivalently, we can define $\Lambda_i = (1+\kappa_i s)\tilde{\Lambda}_i$ and

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

where $b \in \mathbb{R}^+$ is the unique positive solution to $1/2 = \sum_i (\rho b + 2 + \sqrt{(a_i b)^2 + 4)^{-1}}$. Plugging these Λ's into the best reply of the dealer, (18), we obtain demand (**??**) of the proposition.

Now, define $\mu_i = \mu - \sigma\rho z_i$. Given that z_i is drawn iid from a distribution with mean z, μ_i has mean $\mu - \sigma\rho z$. Guess, that all banks issue the same κ when they are ex-ante identical. Since all dealers share the same degree of risk-aversion, ρ, the demand function simplifies to demand function (4).

Bank Funding. Before the auction closes, the bank collects money to fund the auction purchase. It anticipates how everyone behaves in equilibrium. More specifically, it forms an expectation over how much its will win at auction, a_i^*, and at what price, p^*. It also takes an expectation over its inventory position z_i.

It expects to have a balance sheet as in Table 1 (b) after the auction, and chooses κ_i so as to bring the capital ratio after the auction to the target κ^*. This is the case when

$$\kappa^*(1 + \mathbb{E}[p^* a_i^*]) = \kappa_0 + \kappa_i \mathbb{E}[p^* a_i^*]. \tag{19}$$

Given all dealers submit demand schedules as in (**??**), the auction clears when

$$A = \sum_i a_i(p^*) = \sum_i (\Lambda_i + \rho\sigma)^{-1}(\mu - \sigma\rho z_i - (1 + \kappa_i s)p^*).$$

The market clearing price is

$$p^* = \frac{1}{\sum_i (1 + \kappa_i s)(\Lambda_i + \rho\sigma)^{-1}} \left(\sum_i (\Lambda_i + \rho\sigma)^{-1}(\mu - \sigma\rho z_i) - A \right).$$

The bank wins $a_i(p^*) = a_i^*$. By assumption, the function

$$F(\kappa_i) = \kappa^*(1 + \mathbb{E}[p^* a_i^*]) - (\kappa_0 + \kappa_i \mathbb{E}[p^* a_i^*])$$

is strictly decreasing or increasing and crosses the zero line. Therefore, each bank i has a unique best response, characterized by $F(\kappa_i) = 0$. In the unique equilibrium, each bank plays this best response.

Now, define $\mu_i = \mu - \sigma\rho z_i$. Given that z_i is drawn iid from a distribution with mean z, μ_i has mean $\mu - \sigma\rho z$. Guess, that all banks issue the same κ. The market clears at

$$p^* = \frac{1}{N(1 + \kappa s)(\Lambda + \rho\sigma)^{-1}} \Big(\sum_i (\Lambda + \rho\sigma)^{-1}\mu_i - A \Big) \text{ with } \Lambda = \frac{\sigma\rho}{N - 2}$$

$$p^* = \frac{1}{1 + \kappa s} \left(\frac{1}{N} \sum_i \mu_i - \frac{N - 1}{N - 2} \frac{A}{N} \sigma\rho \right).$$

Bank i will win the following amount in equilibrium

$$a_i^* = (\Lambda + \rho\sigma)^{-1}(\mu_i - (1 + \kappa s)p^*) = (\Lambda + \rho\sigma)^{-1} \Big(\mu_i(1 - (\Lambda + \rho\sigma)^{-1}) + \frac{A}{N} \Big)$$

$$a_i^* = \frac{A}{N} + \left(\frac{N - 2}{N - 1} \right) \left(\frac{1}{\sigma\rho} \right) \left[\mu_i - \frac{1}{N} \sum_i \mu_i \right].$$

Combining p^* with a_i^* and taking the expectation, we obtain

$$p^* a_i^* = \frac{c}{1 + \kappa s} \text{ with } c = \frac{A}{N} \left(\mathbb{E}[\mu_i] - \frac{\rho\sigma A(N - 1)}{N(N - 2)} \right).$$

Here we have used that μ_i are iid, and therefore $\mathbb{E}[(\sum_i \mu_i)^2] = N\mathbb{E}[\mu_i^2] + N(N-1)\mathbb{E}[\mu_i\mu_j] = NVar(\mu_i) + N\mathbb{E}[\mu_i]^2 + N(N-1)\mathbb{E}[\mu_i]^2 = NVar(\mu_i) + N^2\mathbb{E}[\mu_i]^2$ and $\mathbb{E}[\sum_i \mu_i * \mu_i] = \mathbb{E}[\mu_i^2 + \mu_i \sum_{j\neq i} \mu_j] = \mathbb{E}[\mu_i]^2 + Var(\mu_i) + (N-1)\mathbb{E}[\mu_i]^2 = N\mathbb{E}[\mu_i]^2 + Var(\mu_i)$. Note that $\mathbb{E}[p^* a_i^*] \geq 0$ because $\mathbb{E}[\mu_i] \geq \frac{\rho\sigma A(N-1)}{N(N-2)}$ by assumption.

With this we can solve for κ such that $F(\kappa_i)$ of Proposition 1 holds:

$$\kappa^*(1 + \mathbb{E}[p^* a_i^*]) = \kappa_0 + \kappa\mathbb{E}[p^* a_i^*] \Rightarrow \kappa = \frac{\kappa^*(1+c) - \kappa_0}{c - s(\kappa^* - \kappa_0)}.$$

We find that all banks indeed choose the same κ. This validates our guess and completes the proof. □

C.2 Proof of Proposition 2

Dealer demand. To derive dealer demand, 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: $a(p) = \left(\frac{N(1-\xi)-1}{N-1}\right)\frac{1}{\sigma\rho}\left(\mu_i - (1+\kappa s)p\right)$.

Bank funding. The market clears when $A = \left(\frac{N(1-\xi)-1}{N-1}\right)\frac{1}{\sigma\rho}\left(\sum_i \mu_i - N(1+\kappa s)p^*\right)$. Thus the market clearing price is

$$p^* = \frac{1}{1+\kappa s}\left(\frac{1}{N}\sum_i \mu_i - \sigma\rho\left(\frac{N-1}{N(1-\xi)-1}\right)\frac{A}{N}\right)$$

The bank wins

$$a_i^* = \frac{A}{N} + \left(\frac{N(1-\xi)-1}{N-1}\right)\left(\frac{1}{\sigma\rho}\right)\left[\mu_i - \frac{1}{N}\sum_i \mu_i\right].$$

Therefore,

$$p^* a_i^*(1+\kappa s) = -\frac{A\mu_i}{N} + \frac{A^2(N-1)\rho\sigma}{N^2(1+N(\xi-1))} + \frac{(\sum_i \mu_i)^2(1+N(\xi-1))}{(N-1)N^2\rho\sigma} + \sum_i \mu_i \frac{2A}{N^2} + \frac{\sum_i \mu_i * \mu_i(-1+N-N\xi)}{(N-1)N\rho\sigma}$$

Taking expectations and using the fact that μ_i are iid, $\mathbb{E}[(\sum_i \mu_i)^2] = N\mathbb{E}[\mu_i^2] + N(N-1)\mathbb{E}[\mu_i\mu_j] = NVar(\mu_i) + N\mathbb{E}[\mu_i]^2 + N(N-1)\mathbb{E}[\mu_i]^2 = NVar(\mu_i) + N^2\mathbb{E}[\mu_i]^2$ and $\mathbb{E}[\sum_i \mu_i * \mu_i] = \mathbb{E}[\mu_i^2 + \mu_i \sum_{j\neq i} \mu_j] = \mathbb{E}[\mu_i]^2 + Var(\mu_i) + (N-1)\mathbb{E}[\mu_i]^2 = N\mathbb{E}[\mu_i]^2 + Var(\mu_i)$,

$$\mathbb{E}[p^* a_i^*] = \frac{\bar{c}}{1+\kappa s} \text{ with } \bar{c} = \frac{A}{N}\left(\mathbb{E}[\mu_i] - \frac{\rho\sigma A(N-1)}{N(N(1-\xi)-1)}\right)$$

$\mathbb{E}[p^* a_i^*] > 0$ because $N \geq 0$ and $\mathbb{E}[\mu_i]N(N(1-\xi)-1) \geq \rho\sigma A(N-1)$.

With this we can solve for κ such that $F(\kappa_i)$ of Proposition 2 holds:

$$\kappa^*(1+\mathbb{E}[p^* a_i^*]) = \kappa_0 + \kappa\mathbb{E}[p^* a_i^*] \Rightarrow \kappa = \frac{\kappa^*(1+\bar{c}) - \kappa_0}{\bar{c} - s(\kappa^* - \kappa_0)}.$$

We find that all banks indeed choose the same κ. This validates our guess and completes the proof. □

C.3 Proof of Proposition 3

The first part of the proof is analogous to the first part of the proof for Proposition 1. The amount a dealer wins at market clearing is $a_i(p^*) = \frac{A}{N}$. $\lambda > 0$ is such that the constraint is satisfied, i.e., $kp^* a_i(p^*) + kx = E$. To obtain the characterization of the proposition, insert the market clearing price and the amount a dealer wins in equilibrium. □

C.4 Proof of Corollary 1

(i) When κs decreases, the demand curve, $a_i(\cdot)$, becomes flatter under both auction formats given that $\frac{\partial a_i(p)}{\partial(\kappa s)} = -(\frac{N-2}{N-1})(\frac{1}{\sigma\rho})p < 0$ in the uniform price auction and $\frac{\partial a_i(p)}{\partial(\kappa s)} = -(\frac{N(1-\xi)-1}{N-1})(\frac{1}{\sigma\rho})p < 0$ in the discriminatory price auction.

(ii) In the uniform price auction the market clears at $p^* = \frac{1}{1+\kappa s}\left(\frac{1}{N}\sum_i \mu_i - \frac{N-1}{N-2}\frac{A}{N}\sigma\rho\right)$. In the discriminatory price auction, the market clears at $p^* = \frac{1}{1+\kappa s}\left(\frac{1}{N}\sum_i \mu_i - \sigma\rho\left(\frac{N-1}{N(1-\xi)-1}\right)\frac{A}{N}\right)$. In both cases, as κs increases p^* decreases.

(iii) Consider the uniform price auction. To derive the degree of price manipulation, 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 $p_T^* = \frac{1}{1+\lambda\kappa}\left(\frac{1}{N}\sum_i \mu_i - \frac{A}{N}\rho\sigma\right)$. With this,

$$ms(\kappa s) = p_T^* - p^* = \frac{1}{1+\kappa s}\left(\frac{A}{N}\right)\left(\frac{1}{N-2}\right)\rho\sigma$$

In the uniform price auction, the price difference between the truthful and strategic market price is the same as the average amount a bidder shades at market clearance:

$$ms(\kappa s) = \frac{1}{N}\sum_i shading(a_i^*).$$

Here $shading(a_i^*)$ is the difference between the price bidder i offer for amount a_i^* if she were price-taking and the price she actually offers.

Analogously, we can derive the expression for the discriminatory price auction. Here $p_T^* = \frac{1}{1+\kappa s}(\mu + \frac{\rho\sigma}{\xi-1}(\frac{A}{N} + \frac{1}{N}\sum_i z_i - \xi\overline{z}))$. With this,

$$ms(\kappa s) = p_T^* - p^* = \frac{1}{1+\kappa s}\left(\frac{A}{N}\right)\left(\frac{\xi}{\xi-1}\right)\rho\sigma.$$

In the discriminatory price auction, $ms(\kappa s)$, is not the same as $\frac{1}{N}\sum_i shading(a_i^*)$. Instead,

$$\frac{1}{N}\sum_i shading(a_i^*) = \frac{\rho\sigma}{(1+\kappa s)}\left[\frac{\xi}{\xi-1}(\overline{z} - \frac{1}{N}\sum_i z_i)\right]. \quad \square$$

C.5 Proof of Corollary 3

Consider the first two statements and assume absolute risk aversion and demand. Keeping N constant, the main factor that determines the slope of demand is $k\lambda$. This decreases in ρ, decreases in E, and increases in k. To see the later, take the

derivative:

$$\frac{\partial[k\lambda]]}{\partial k} = \frac{AE\mu}{N(E-kx)^2} - \frac{A^2E(N-1)\rho\sigma}{(N-2)N^2(E-kx)^2} > 0 \Leftrightarrow \mu - \frac{A}{N}\left(\frac{N-1}{N-2}\right)\rho\sigma > 0$$

which is the case when $p^* > 0$.

Now assume dealers have relative risk aversion and demand. As E increases, $k\lambda$ decreases due to a direct effect. In addition, there is an indirect effect since ρ decreases. This increases $k\lambda$. If γ_i is sufficiently large, the second effect dominates.

The statements about the market clearing price and price manipulation follow analogously to the proof of Corollary 1. □

D Detailed data description

Variables in LR. The LR is the ratio of regulatory capital, namely Tier 1, over total leverage exposure.

Tier 1 capital consists of common equity Tier 1 capital (sum of common shares and stock surplus, retained earnings, other comprehensive income, qualifying minority interest and regulatory adjustments) and additional Tier 1 capital (sum of capital instruments meeting the criteria for additional Tier 1 and related surplus, additional 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.

Alternative slope measures. For one, we replace $\max_k\{a_{itsk}\}$ in (12) by the amount each dealer asked for at the highest step, k_i^*, it ever won: $a_{itsk_i^*}$. Second, we cap $\max_k\{a_{itsk}\}$ by the largest amount a dealer ever won (in % of supply). Third, we compute the local slope around the point at which the market clears. For this, we first find the market clearing yield of an auction, $yield_{ts}^C$. 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, $yield_{ts}^{UB} = yield_{ts}^C + 0.001$, and

the yield that lies just below the clearing yield: $yield_{ts}^{LB} = yield_{ts}^{C} - 0.001$. 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.

E Additional empirical evidence

Additional data. In the main text, we restrict our sample period form January 2015 onward because the LR ratios were not collected before then. Here, we expand the sample period to start in January 2002, and collect additional balance sheet information. We obtain monthly data of total cash and reserve holdings, total on-balance sheet assets, shareholder capital holdings, and capital ratios from 01/01/2002 until 02/01/2022 from a data source, called M4.[31]

The cash and reserve holdings include gold coin, gold and silver bullion held in Canada and elsewhere, gold and silver certificates held as investments, precious metals, Bank of Canada notes on hand, foreign currency notes, Canadian coin on hand, foreign coin held in Canada and elsewhere (foreign coin is to be reported as foreign currency, but U.S. coin in circulation in Canada need not be segregated unless amounts are material), all completed deposit transactions with Bank of Canada, including Large-Value Transfer System (LVTS), Special Deposit Account (SDA) and Automated Clearing and Settlement System (ACSS) component balances.

The total on-balance sheet assets include cash and cash equivalences, securities, loans, customers liability under acceptances, less allowance for expected credit losses, land, buildings, and equipment, less accumulated depreciation, and other assets, less allowance for expected credit losses where applicable.

The shareholder capital holdings consist of preferred Shares, common shares, contributed surplus, retained earnings, non-controlling interests, and accumulated other comprehensive income (loss).

[31]For detailed information, see `www.osfi-bsif.gc.ca/Eng/fi-if/rtn-rlv/fr-rf/dti-id/Pages/M4.aspx`, accessed on 05/31/2022.

Appendix Table 5: Effect of capital on the slope of demand

	(OLS)	(FE1)	(FE2)
capital	0.0334***	0.0159***	0.0208***
	(0.000816)	(0.000435)	(0.000866)
constant	0.356***	0.768***	0.652***
	(0.0265)	(0.0131)	(0.0218)
day-security fixed effect (ζ_{ts})	–	✓	✓
dealer fixed effect (ζ_i)	–	–	✓
Observations	18162	18162	18162
Adjusted R^2	0.084	0.817	0.834

Table 5 shows results of regressing the slope measure on equity-capital, $slope_{its} = \alpha + \gamma capital_{mi} + \zeta_{ts} + \zeta_i + \epsilon_{its}$. In (OLS) we present the OLS regression. In (FE1) we add the day-security fixed effect and in (FE2) the dealer-fixed effect. The slope measure in bn C$/% and capital in bn C$. Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Equity capital. To gather evidence that demand changes when equity capital increases, we analyze if the slope of dealer i's demand for security s on day t correlates with its bank's equity capital in that month, m:

$$slope_{its} = \alpha + \gamma capital_{mi} + \zeta_{ts} + \zeta_i + \epsilon_{its}$$

To ensure that the effect is not driven by unobservable demand or supply factors that are specific to a bank, the security, or the time period, we include dealer, ζ_i, and date-security fixed effects, ζ_{ts}. Therefore, our parameter of interest, γ, is identified from variation across banks within a month after controlling for time invariant differences between banks.

In line with our hypothesis, we estimate that β is positive (see Table 5 column (1) and Appendix Table 7 for alternative slope measures). When capital increases by 1 billion C$, the slope increases by roughly 0.02 billion/%. This is a sizable effect compared to the average amount a dealer wins at auction (C$277 million).

The estimated effect is causal when assuming that the slope is uncorrelated with

the error term, conditional on day-security fixed effects: $\mathbb{E}[capital_{im}\epsilon_{its}|\zeta_{ms}\zeta_i] = 0$. This assumption would be violated if there are (to the econometrician) unobservable shocks that lead dealers to hold higher capital and change their bids. For instance, if there is an unobservable shock that triggers the dealer to simultaneously decrease their capital holdings and submit a flatter demand, the γ estimate would be upward-biased.

In our context, such a bias is likely small. The reason is that dealers have direct control over how much they bid at auction, but not over how much capital or assets the entire bank holds at the company holding level, which is largely affected by the degree of bank risk aversion.

Slope measure correlates with VIX. To further motivate that the slope may be informative about dealer capitalization, we show that the slope correlates with a commonly used measures in the literature, the VIX (see Table Appendix 6). It indicates how much capital banks hold, because it correlates with balance sheet information (e.g., Adrian and Shin (2010); Ang et al. (2011); Ben-David et al. (2011); Fleckenstein and Longstaff (2020)). It also can inform us about how costly it is for the bank to hold capital. The reason is that theory predicts that higher volatility, i.e., a higher VIX, tightens the banks' constraints and thereby reduces their liquidity-provision capacity (see Gromb and Vayanos (2002); Brunnermeier and Pedersen (2009)). When constraints are tighter, in turn, our model predicts that the slope should become steeper. Thus, finding a positive correlation between the VIX and the slopes is in line with our hypothesis.

Appendix Table 6: Correlation between the slopes and VIX

	(1)	(2)	(3)
slope	0.555***	0.568***	0.607***
	(0.0258)	(0.0567)	(0.0614)
constant	19.28***	19.26***	19.21***
	(0.0752)	(0.0694)	(0.0751)
dealer FE	–	✓	✓
days-to-mat. FE	–	–	✓
Observations	16856	16856	16856
Adjusted R^2	0.027	0.027	0.214

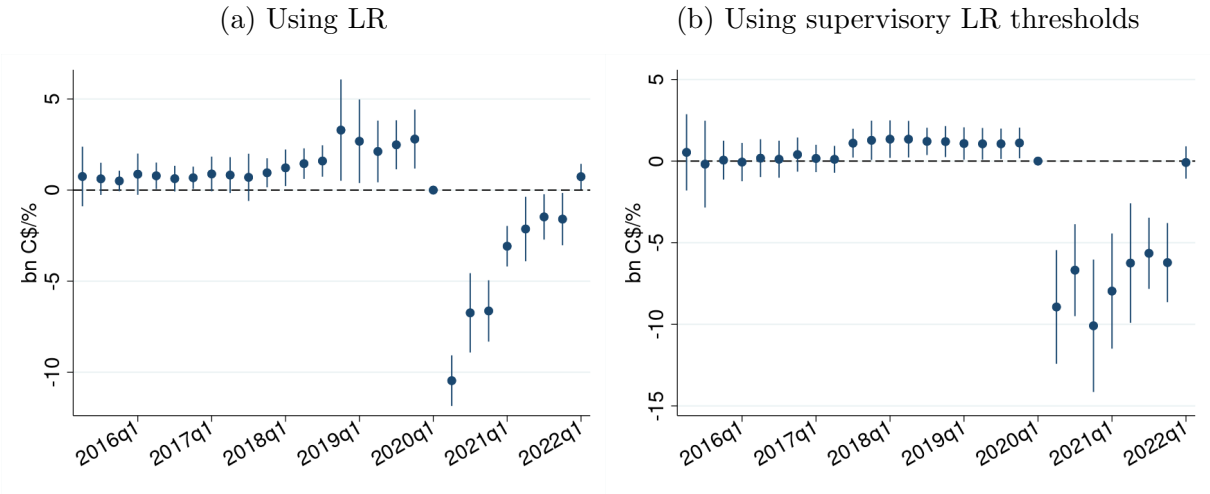
Table 6 displays estimation results when regressing VIX_t on $slope_{its}$. All correlations are higher (close to 1) when excluding the years of the COVID-pandemic, 2020-2022. In column (1), we show an OLS regression. In column (2), we include a dealer fixed effect. In column (3), we include dealer and days-to-maturity fixed effects. Standard errors are in parentheses. They are clustered at the dealer level in columns (2)-(3). * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix Table 7: Effect of capital on the slope of demand, alternative slope measures

	(1)	(1)	(2)
capital	0.0208***	0.00984***	0.532***
	(0.0107)	(0.0164)	(0.190)
constant	0.649***	0.192***	35.86***
	(0.252)	(0.0847)	(4.723)
day-security fixed effect (ζ_{ts})	✓	✓	✓
dealer fixed effect (ζ_i)	✓	✓	✓
Observations	18162	18162	15169
Adjusted R^2	0.831	0.823	0.330

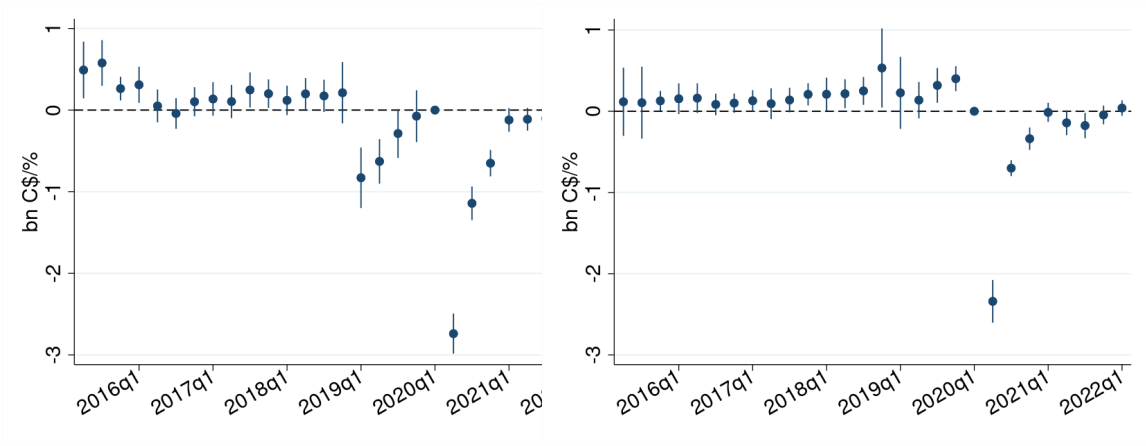
Appendix Figure 7 shows results of regressing our alternative slope measures on equity-capital, $slope_{its} = \alpha + \gamma capital_{mi} + \zeta_{ts} + \zeta_i + \epsilon_{its}$. For the slope measure used in (1), we $\max_k\{a_{itsk}\}$ in (12) by the demand at the dealer asked for at the highest step it ever won. In (2), we cap this amount by the largest amount ever won (in % of supply). In (3), we use the local slope measure. All are measured in billion C$/percent, but easily comparable in size. Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix Figure A1: Change in the slope with dealer fixed effects



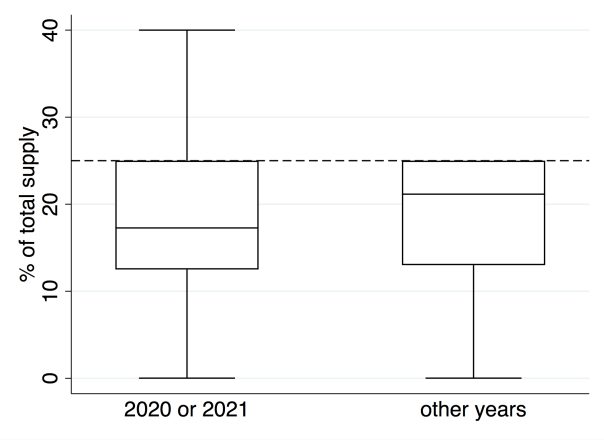
Appendix Figure A1a shows the γ_k estimates and 95% confidence intervals of the regression (13): $slope_{iqs} = \alpha + \sum_{k=-K}^{K} \gamma_k * D_k * LR_{ik} + \zeta_{qs} + \zeta_i + \epsilon_{iqs}$. Appendix Figure A1b replaces LR_{ik} by the institution-specific Basel III threshold. All magnitudes are relative to the benchmark in 2020q1. The slopes are measured in billion C$/percent. Standard errors are clustered on the dealer level.

Appendix Figure A2: Event study with maximal demand, i.e., $\max_k\{a_{i,t,s,k}\}$



Appendix Figure A2a shows the γ_k estimates and 95% confidence intervals of the regression (13): $q_max_{iqs} = \alpha + \sum_{k=-K}^{K} \gamma_k * D_k * LR_{ik} + \zeta_{qs} + \epsilon_{iqs}$ with q_max_{iqs} as average of $\max_k\{a_{itsk}\}$ per a dealer/quarter/security. In Appendix Figure A2b, we add a dealer fixed effect. Demand is measured in billion C$. Standard errors are clustered at the dealer level in (b).

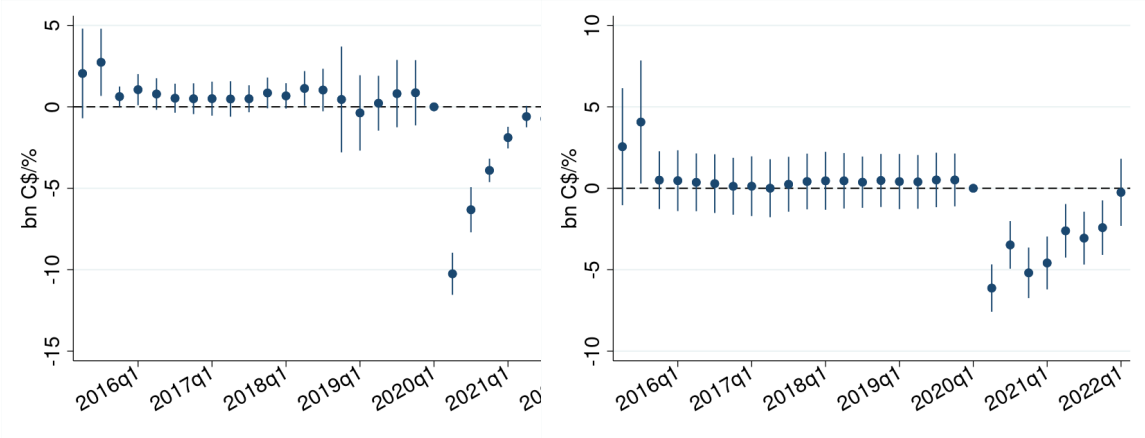
Appendix Figure A3: Maximal dealer demand as % of total supply



Appendix Figure A3 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 A4: Event study with unconstrained dealers (w.r.t. bidding limits)

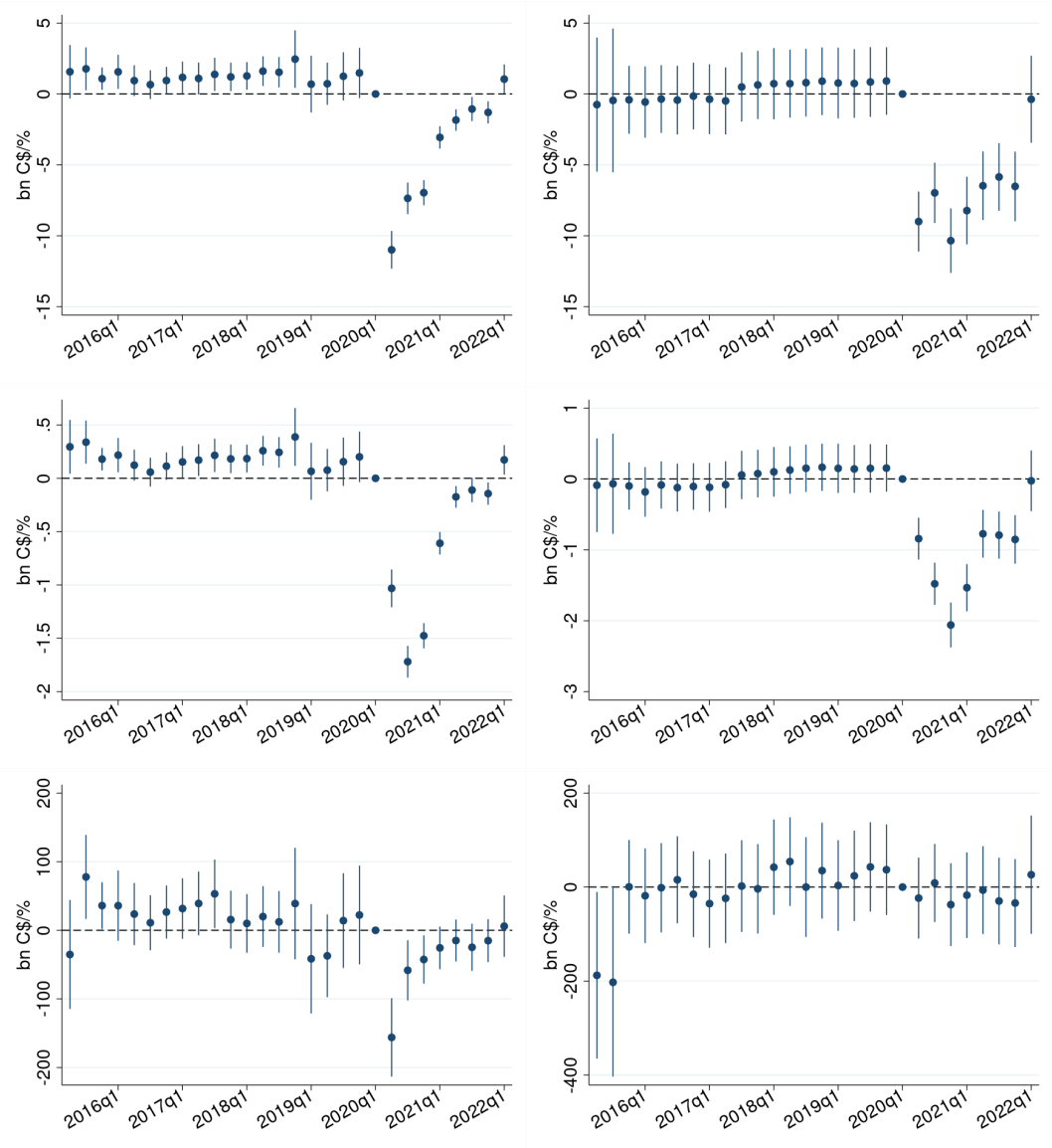
(a) With LR (b) With supervisory LR thresholds



Appendix Figure A4 is analogous to Figure 3a. It shows the γ_k estimates and 95% confidence intervals of the regression (13): $slope_{iqs} = \alpha + \sum_{k=-K}^{K} \gamma_k * D_k * LR_{ik} + \zeta_{qs} + \epsilon_{iqs}$. Figure 3b replaces LR_{ik} by the institution-specific Basel III threshold. All magnitudes are relative to the benchmark in 2020q1. The slopes are measured in billion C$/percent.

Appendix Figure A5: Event study with alternative slope measures

(a) Using LR (b) Using supervisory LR thresholds



Appendix Figure A5 is analogous to Figure 3a, but uses different slope measures. It shows the γ_k estimates and 95% confidence intervals of the regression (13): $slope^{other}_{iqs} = \alpha + \sum_{k=-K}^{K} \gamma_k * D_k * LR_{ik} + \zeta_{qs} + \epsilon_{iqs}$ 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 (12) 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 the local slope measure. All magnitudes are relative to the benchmark in 2020q1. The slopes are measured in billion C$/percent. All graphs look similar when we include dealer fixed effects.