Why We Should Start Thinking of Illiquidity Spells in Over-the-Counter Markets in Terms of Oligopolistic Inefficiency

Assa Cohen *
Sy Syms School of Business, Yeshiva University † ‡

October 11, 2025

Abstract

The paper argues that systemic distress reduces liquidity in over-the-counter (OTC) markets by changing dealers' strategic incentives. In crises, dealers exploit stressed customers' inelastic demand to extract higher markups, resulting in larger bid-ask spreads. The markups further produce monopsony-like reductions in traded quantities. Using Regulatory TRACE data on U.S. corporate bonds with dealer identities, I document pronounced bond-level concentration and market segmentation. I show that bonds with greater ex-ante concentration experience larger crisis-era increases in dealer markups (the customer–dealer price relative to the interdealer price) and deeper volume declines. I develop a model in which dealers that dominate a given security are those more informed about its value. The model reveals that adverse selection, by thinning competition from uninformed dealers, is the crucial conduit through which systemic distress raises dealer markups during a crisis. A calibration to March 2020 matches the magnitude and cross-section of spread and volume changes, and counterfactuals show similar liquidity losses even when dealer capacity is fixed at pre-crisis levels.

Keywords: market power, OTC markets, market freeze, information acquisition, corporate bonds.

JEL classification:: E44, G01, G11, G12, G21.

*Email: assa.cohen@yu.edu

†Former Affiliation: Federal Reserve Bank of Philadelphia. The views expressed herein are solely those of the author and do not necessarily reflect the views of the Federal Reserve Bank of Philadelphia or the Federal Reserve System. Any errors and omissions are my own.

‡I would like to express my gratitude to Guillermo Ordonez, Itay Goldstein, Jesús Fernández-Villaverde, Harold Cole, and Benjamin Lester for their invaluable advice and ongoing support. I would also like to thank the seminar participants at the Federal Reserve Board, LeBow College of Business, the Office of Financial Research, Sy Syms School of Business, Wharton School of Business, Federal Reserve Bank of Philadelphia, and the Economics Department at the University of Pennsylvania. All mistakes are my own.

1 Introduction

Economic crises are often marked by a sudden and persistent loss of liquidity in over-the-counter (OTC) financial markets. These illiquidity spells, which often last for months or even years, are characterized by an increase in the cost of trade (big-ask spread) alongside a decline in trade volume and new issuance. Notable examples include the disruptions to trade at the commercial paper market during the 1969–1970 recession, the junk bond market in the 1990–1991 recession, the mortgage-backed securities market in the 2008-2009 financial crisis, and more recently, the corporate bonds market during the March 2020 COVID-19 crisis. These illiquidity spells worsen a crises by restricting credit to real economic activity and spilling over to disrupt the performance of other markets and financial institutions, a phenomenon that was especially apparent during 2008-2009.

It is often argued that the propensity of trade in OTC markets to decline during a crisis emerges from the decentralized trading protocol itself. The claim is supported by the contrast between OTC performance in crisis vs. the performance of centralized markets, which usually maintain orderly trading activity. Many of these accounts (for instance O'Hara and Zhou (2021), Dick-Nielsen and Rossi (2019), Duffie (2020)) pointed to the reliance on dealer intermediation as a potential source of OTC fragility. In a crisis, dealers face tighter funding and higher risk, which increases the cost of taking securities into their balance sheet as a part of market making. To compensate, they charge wider bid-ask spreads, which supresses trade volume.

Yet, empirical patterns that characterize the behavior of OTC markets during crisis indicate that widening of the spreads is not merely reflecting a rise in dealers holding costs. Specifically, during a crisis we witness substantial widening of the difference between the price a dealer pays another dealer for a security and the lower price it pays a customer for the same security. For example, as shown below, in the US corporate bonds market, this difference almost doubles from 23.5 bps in normal times to 41.6 bps during a crisis. Since the holding cost is the same whether the security is purchased from another dealer or from a customer, the widening of the gap is not likely to be the result of higher holding costs. Rather, it appears more like an increase in the *markups* that dealers impose on customers, who are less integrated into the market.

Thus, in this paper I set forth a theory that views the rise in spreads in OTC markets during a crisis as driven by dealers' stratigic choice to charge higher profit margins for their services. Accordingly, the decline in trade volume is merely an instance of a non-discrimating oligopsony persuit of rents resulting in a decline in quantity. Critically, the theory implies that a intermediation can lead to a loss of liquidity even if dealers capacity to take securities into their balance sheet is unaffected. Policy-wise, the theory implies that injecting funds into the dealer sector, using tools such as the Fed's Primary Dealer Credit Facility (PDCF), may not suffice to extricate an OTC market from an illiquidity spell.

The theory contends that OTC markets lose liquidity during a crisis because systemic distress worsens disruptions to trade caused by intermediaries market power. I suggests three mechanisms through which distress exacerbates such disruptions: (i) heightened demand for liquidity incentivizes dealers to exercise their market power more aggresivly , (ii) rise in adverse selection leads uninformed dealers to withdraw from the trade, limiting competition, and (iii) tighter capacity constraints preventing some dealers from trading, further eroding competition. Below, I provide detailed intuition for each, beginning with the demand channel, whose logic merits deeper initial exposition.

To get a firmer intuitive understanding of the demand channel, consider the a dealer who effectively monopolizes trade in a specific security. That dealer faces a trade-off between charging higher spreads (bidding low) and increasing the quantity traded. During a crisis, distressed investors are eager to sell, even at a significant discount. From the dealer's perspective, this means that an increase in the spreads she charges will have a weaker impact on the volume of trade that she gets to facilitate. This, in turn, makes it optimal to submit lower bids that only appeal to these distressed players. Doing so will result in higher realized spreads and a decline in the volume of trades. Note that this is just a manifestation of a more general principle - as demand becomes less elastic, a non-discrimnating monopsony (or any player with market power) transitions towards charging higher mark-ups at the expense of reducing volume.

Now, to clarify the adverse selection mechanism, consider an example in which a dealer is not a monopoly in trading a specific security, but rather the only intermediary that knows its true value. Competing dealers, uncertain about that value, bid cautiously to mitigate losses from adverse-selection. This allows the informed dealer to submit fairly low quotes and still win most of the trade volume. When a crisis erupts, rising default risk widens the valuation gap between safe and risky assets, amplifying potential adverse-selection losses. Uninformed dealers respond by demanding even steeper discounts on securities they cannot accurately price. Their retrenchment enhances the informed dealer's advantage, enabling her to further raise markups while continuing to dominate trade.

Lastly, in a crisis scarce funding and lower risk tolerance will lead some dealers to abstain from taking securities into their balance sheets hence strengthening the competitive advantage of other dealers who remain in the market. I will argue here that this mechanism, that is tightly connected to higher holding costs, is not essential for systemic distress to impair competition and create a dire decline in liquidity in OTC markets.

To test and contextulize this theory I conduct an empirical analysis of competition and concentration in the U.S. corporate bond market using Regulatory TRACE data. This restricted version of TRACE, that includes dealer identities, reveals significant concentration and market segmentation that traditional market-wide measures obscure. While numerous dealers participate at the market-wide level, trading activity for any specific bond is typically handled only by a few. I denonstrate this segmentation through the contrast between the low market-wide Herfindahl-Hirschman Index (HHI) of 0.05, indicating negligible overall concentration, and the much higher median bond-level HHI of 0.36, comparable to a market with only three dealers sharing trade volume equally. I further document high levels of dealer specilization, with each delaer trading concentrated in a fairly small subset of bonds. The segmenation implies that a customer who wishes to sell a security might face a limited number of potential buyers among the broker-dealers. Alongside, I show that dealers tend to specilize by issuer and by industry and that dealers with the largest volume share in a specific bond typically charge narrower spreads on trading it.

Alongside, I observe that dealers specilize in trading bonds of specific issuers and issuers from specific industires, a clustering pattern consistent with economies of scope in information. The finding suggests that the dealers that dominate trading in a given bond might be those that are familiar with it. Because dealers face adverse-selection risk and typically recoup expected losses through wider spreads, better-informed dealers can afford to quote more aggressive (higher bid / lower ask) prices and, in turn, attract a larger share of order flow. Consistent with this hypothesis, I document that dealers with the largest volume share in a specific bond typically charge narrower spreads on trading it.

Furthermore, I find that bonds with higher concentration exhibited a greater deterioation of liquidity during the March 2020 COVID-19 crisis. I find that a 10 bps increase in a bond's HHI is associated with a 9 bps increase in the markup that dealers charge when purchasing the bond. The result persists when controlling for potential confounders, including the bond attributes such as rating and liquidity, the identity of the dealer, trade volume, and date of trade. I document similar patterns also during the 2008-2009 financial crisis. Since this analysis is does not rely on random assignment or quasi-exogenous variation in concentration, the evidence should be viewed as suggestive rather than conclusive. Yet, keeping that in mind, the finding provides support to the claim that market power limits liquidity provision in OTC markets during a crisis.

In view of these empirical findings, I set forth and calibrate a simplified model of customer-to-dealer trades in OTC markets. The model serves a dual purpose. First, it is used to test whether a theory that regards crisis dynamics in OTC markets as driven mostly by the stratigic bidding of broker-dealers can rationalize the data. Second, it is applied to study relations of dependence and amplification between three channels through which systemic distress rises spreads in the context of dealer mark power: (1) heightned demand for liquidity, (2) adverse selection due to elevated risk, and (3) tightening of dealers capacity constratins.

Based on the seminal imperfect competition Varian (1980) and Burdett and Judd (1983) the model depicts trade as an auction in which a customer solicits bids from all dealers. Each dealer is "not available" to quote with probability π, capturing search frictions and balance-sheet constraints. I follow Camargo and Lester (2014), to incorporate into this framework assymetric information and assume that with some probability the security is a “lemon”. Customers and a minority of informed dealers observe quality; the majority dealers remain uninformed. These uninformed dealers must shade bids by an amount that compensates for expected losses from buying “lemons”, while the informed, that are not subject to adverse selection, do not. This simple asymmetry endogenously yields a highly concentrated order flow: informed dealers quote more aggressively, win most (but not all) trades in their niche bonds, and charge lower spreads - replicating the patterns seen in the data.

Two regimes arise. When adverse selection risk is low, a quasi-pooling equilibrium emerges, where uninformed dealers bid for unfamiliar assets using profits from “good” securities to offset losses from purchasing “lemons”. The competition that they pose disciplines informed dealers and keeps customer spreads modest. However, when adverse selection risk rises beyond a certain threshold uninformed dealers exit the market due to an Akerlof type “lemon market” mechanism. The remaining informed dealers constitue an oligopsony: with rival bidders gone, they post low bids that only the most liquidity-pressed customers accept. Spreads jump and volumes falls even if dealer balance-sheet capacity (π) remains unchanged.

The model reveals that customer distress is transmitted to wider bid–ask spreads only when adverse selection is severe. The presence of distressed customers incentivizes dealers to submit low bids aimed specifically at those players. However, when adverse selection is mild, any dealer is willing to purchase the asset at a discount that compensates for the expected loss from buying an unfamiliar security. This option of selling for that discount effectively caps the spread a dealer can charge before being undercut by competitors.

I calibrate the model to customer sales of corporate before and during the COVID-19 crisis (January 2019 to April 2020). First, I determine moments pertaining to asset composition directly from the data using the probabilities of a bond downgrade and its expected impact on the bond price in the interdealer market. Then, I estimate the remaining parameters by targetting the behaviour of dealer markups in markets with varying levels of competition (HHI) before and during the COVID-19 crisis. The model replicates the differences in the volume response to the crisis across those markets almost perfectly, although these differences were not used as targets for the calibration.

Counterfactual analysis of the model reveals that the rise of risk premiums during the crisis, reflected in a dramatic widening of the interdealer prices differences between bonds with different rating, was essential for the rise in dealer markups during the COVID-19 crisis. This rise was dramatic enough to lead to a regime change towards the quasi-Akerlof "lemon market" equilibrium. In its absence, the heightened demand for liquidity and the tightening of dealer capacity constraints would have only a slight impact on dealer. In contrast, the counterfactuals reveal even if dealers' capacity constraints would maintain their pre-crisis levels during the COVID-19 crisis, heightened demand for liquidity and changes in asset composition alone would bring about a substantial deterioration of trading conditions.

The paper is organized as follows: section 2 presents stylized facts and analysis pertaining to the concentration in the dealer sector and its origin, section 3 demonstrates the association between concentration and rising dealer markups during a crisis, section 4 presents the model and derives some theoratical results, section 5 presents the calibration and some coutnerfactuals, and section 6 concludes.

Literature Review

The paper is a part of the literature that addresses the question: "Why are OTC markets susceptible to failure during a crisis?". The literature has pointed out two causes that may underlie it. The first is *opacity.* Assets traded in OTC markets are characterized by high levels of heterogeneity and complexity. Also, the decentralized nature of the trade makes it harder to learn from actions taken by others (for instance, quotes are not published). The opacity generates adverse selection. An economic downturn exacerbates it by increasing the likelihood of defaults and imposing a more significant penalty for purchasing a risky asset. Hence, trade is diminished through an Akerlof (1978) lemon market mechanism. Papers that discuss such a mechanism include, for instance, Guerrieri and Shimer (2014), Camargo and Lester (2014), and Zou (2019)).

The second cause discussed in the literature *limits on dealers' capacity.* Trade in OTC markets is facilitated through dealers. A crisis weakens dealers' balance sheets. As a result, they are less able to bear the risk involved in purchasing securities as a part of their market-making activity. They may also face a shortage of capital. The increase in dealers' costs will prevent them from meeting the heightened liquidity needs that emerge in systemic distress. Much of the literature that discusses limits on dealer capacity evolved in the context of the debate about the post-2008 regulation that placed new restrictions on bank-affiliated dealers. Papers such as Dick-Nielsen and Rossi (2019) or Bao et al. (2018) compare the response of the market to street events (i.e., index exclusion or downgrades) before and after the regulation kicked in. They show that following the regulations spreads increase faster in response to heightened demand for liquidity. In addition, the effect is more pronounced with bank-affiliated dealers, that is, those affected by the regulation.

The paper contributes to this literature by suggesting a third cause: monopolistic inefficiency. This is the first paper to tell that such a mechanism plays a crucial role in generating "cold spells" in OTC markets. By that, it highlights that competition (or its absence) in OTC markets is critical for understanding their stability. In this context, the paper

The paper is strongly related to the rich and fertile literature that applied search models to the study of OTC markets that originates in the canonical papers of Duffie et al. (2005) and Lagos and Rocheteau (2009). It shares with it the view that spreads in OTC markets embed markups charged by dealers. However, it suggests a different framework of thinking about the origin of the market power that enables markups to emerge. The search literature contends that a dealer's power over customers originates from search frictions that make it hard for the customer to find other dealers to trade with. Note that, at face value, this story does not appear very compelling. In contrast to finding a job (another prime application of search theory) that may require contacting hundreds or even thousands of firms to reach most openings, finding a dealer willing to buy should be more straightforward. More than 90% of the trade in the US Corporate Bonds Market is accounted for by the top 20 dealers. These are large and well-known players, and merely finding them requires no more than a phone call or an email [1]. In contrast, the paper suggests that the obstacle in OTC markets is

[1]Indeed, the Duffie et al. (2005) seminal paper states that the search frictions are an abstraction that is underpinned by a more complex mechanism, such as a limitation on clearance or time required for dealers to acquire information about the security traded

that few dealers are willing to purchase each security. In other words, each customer faces only very few incumbents. In such circumstances, markups can arise without substantial search frictions (e.g., Cournot competition).

The paper also belongs to the literature that studies the impact of dealer market power on spreads. One segment of this literature consists of empirical papers attempting to disentangle dealer spreads into cost and markup components. For instance, Green et al. (2007) applies a production frontier setting to argue that the markup of a transaction is the difference between the spread taken by the dealer and the smallest spread charged for a similar transaction that occurred at about the same time. The novelty of this paper is inferring market power from *volume*. Since I gauge market power separately from spreads, I can better learn how one affects the other. Specifically, I present evidence of a clear and sizeable correlation between concentration in OTC markets and the response of bids to systemic distress. In this context, the documentation of the concentration in OTC markets has a solid connection to the documentation of a similar pattern among market-makers in stock markets by Schultz (2003). Like Schultz, I argue that the concentration results from informed players dominating the market-making activity.

The paper is a part of the literature on information acquisition. It applies Van Nieuwerburgh and Veldkamp (2010) and Veldkamp (2014) theory about under-diversification to explain concentration in OTC. According to the theory, costly information acquisition implies payoffs to specialization. An investor may prefer to hold a narrow portfolio since doing so allows her to become highly informed about her holdings. The seminal paper by Kacperczyk et al. (2005) demonstrates such under-diversification among mutual funds, and documents that funds that specialized in specific industries exhibit better performance. In an OTC setting, a recent paper by Chaderina and Glode (2022) demonstrates how expertise contributes to a dealer's return by increasing its order flow. That, in turn, allows the dealer to extract higher rents from encounters with less sophisticated investors.

2 Data

I use the Regulatory TRACE data of the US Corporate Bonds Market (2006–2020). TRACE is a transaction-level dataset collected by FINRA based on reports broker-dealers are required to submit for trades executed not through an exchange. Since regulations restrict market participants from trading without dealers, TRACE provides comprehensive coverage of OTC bond trades. The data includes rich detail about each transaction, including CUSIP identifier, trade time, price, and volume. Additionally, the restricted regulatory version of TRACE used in this study identifies the dealer executing the trade, which is essential for constructing concentration measures. I merge the TRACE dataset with the Mergent FISD database to enrich it with detailed bond characteristics and bond-rating histories.

I follow common data filtering and sampling procedures for TRACE used in prior literature (). My analysis begins in 2006 since earlier TRACE data has limited coverage and lower quality. I adopt standard filtering methods, such as those proposed by **?** or Choi et al. (2021), so that each observation represents a unique transaction rather than a single report. My subsample consists of bond issued in U.S. dollars by U.S. firms in one of three broad FISD industry groups: industrial, financial, or utility. Bonds with specific features known to significantly affect pricing, such as perpetual, Yankee, or asset-backed bonds, are excluded, as well as bonds that cannot be matched with Mergent FISD. After these cleaning steps, the final sample consists of 121 million observations. Additional details on data preparation are in the appendix.

I categorize trades into two types: agency and principal trades. In agency trades, dealers purchase bonds only after securing a buyer, while in principal trades, dealers hold the bonds in inventory while searching for one. I classify a trade as agency trade if it was reported as such by a dealer or if the dealer resold the bond within 15 minutes after purchasing it. My analysis focuses on principal trades, which accounted for over 70% of total trade volume during 2019–2020, and that are channel through which customers recieve *immedate* injection of liquidity from dealers (see Dick-Nielsen and Rossi (2019)).

3 Anatomy of concentration

The data indicates substantial market segmentation, manifested in a gap between low concentration at the market level vs. fairly elevated concentration at the bond level. Thus, while the market has numerous broker-dealers the trade in each bond is dominated by a few.

I measure concentration using the Herfindahl – Hirschman Index (HHI), a common tool used in the literature to summarize to which extent is the activity in the market dominated by only a few players (). The analysis in this section focuses on trades in the year 2019 conducted by the largest 50 dealers in the market. That dealers account for constitute more than 99.5% of all trades. (check the code - I am quite sure that I included only bonds traded at least 5 times a year - important to indicate it clearly).

Let $V_{b,t}$ be the total volume of bond b traded in year t. Let $v_{d,b,t}$ be the volume of the bonds traded by dealer d in year y. Define the dealer share as

$$s_{d,b,t} = \frac{v_{d,b,t}}{V_{b,t}}.$$

Based, on it, the Herfindahl-Hirschman Index (HHI) at the bond level is defined as

$$HHI_{b,t} = \sum_{d=1}^{n} s_{d,b,t}^2. \tag{1}$$

Figure 1 exhibits an analogous plot for HHI. The median HHI is about 0.38. To get an intuitive understanding of it, imagine a market that only has three traders. The first trader is responsible for 40% of all volume, the second one also for 40%, and the third one for 20%. This highly concentrated fictitious market has an HHI of 0.36, which is a lower level than the one found for the median bond market.

From the plot we see that the median bond HHI is 0.36, that is, the concentration level is similar to a market with 3 participants splitting the trade evenly with each other. When we limit our attention only to trades with customer the concentration level rises, and when we limit to principal capacity it rises further so that the median bond HHI is 0.5, similar to what

Concentration in the US Corporate Bonds Market (measured by HHI)

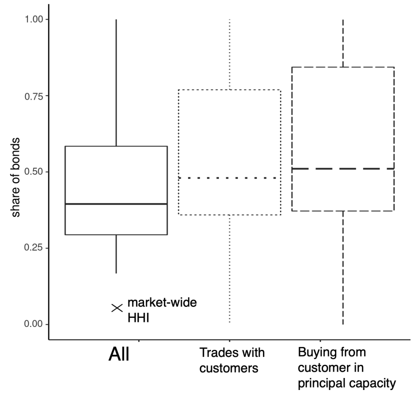

Figure 1: Distribution of the bond-level HHI, 2006-2020.
Note: The data relied upon to generate this figure was TRACE Data provided by FINRA's TRACE System.

we get in a market with just 2 market participants, each accounting for a half of the trade. This better reflects the options available to a customer trying to attain immideate liquidity by selling to a dealer, and it is quite high. The rise in the HHI does not originate merely from taking a small subset of bonds; Rather, it is also because: (i) designated players that intermediate trades between dealers (mostly, ATS), and (ii) trading some bonds in agency but not principal capacity. An analogous analysis that measures concentration using the share of the three largest players in each market (CR3) appears in the appendix.

Further, it is possible to see that concentrated markets account for a sizeable part of total trade in corporate bonds. Figure 2 plots the cumulative volume (y-axis) that was bought by the dealer in principal capacity when trading bonds with an HH-index of h of below it (x-axis, HHI)). About 50% of the volume sold by customers (bought by dealers) in the year 2019 was generated in trades of bonds with an HH-index of 0.4 or more.

3.0.1 Dealer Specilization

The high market segmentation is also manifested in dealer specilization (rephrase this to say that dealer specilization is implied by bond-level (but not market) concentration. To gauge it, I define a dealer d as specializing in trading of bond b if its share in volume traded of that bond is at least three times greater than his share in the total volume of trade in the market.

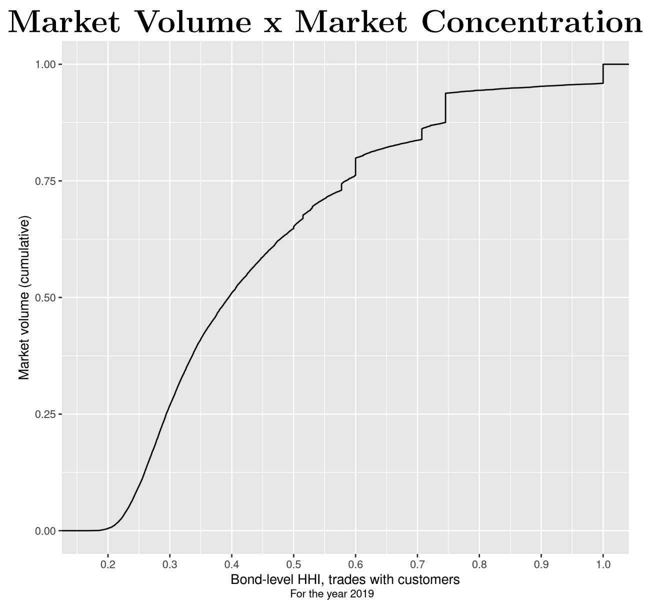

Figure 2: Markets with high concentration account for a substantial share of total market volume.
Note: The data relied upon to generate this figure was TRACE Data provided by FINRA's TRACE System.

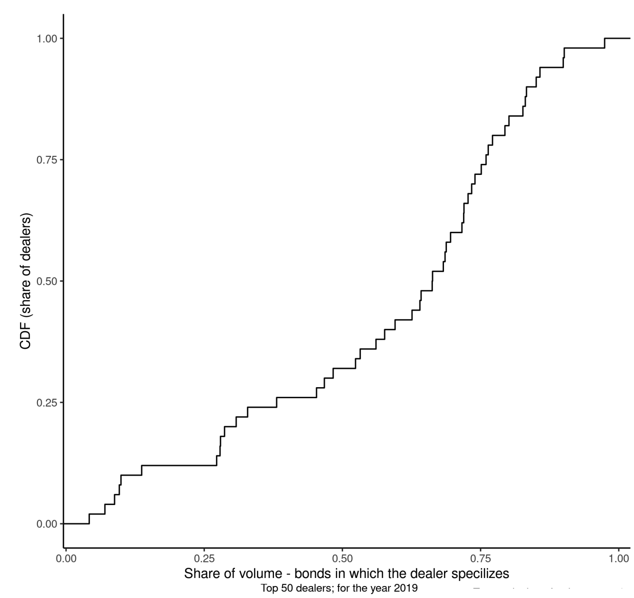

Figure 3: A dealer trades mostly in bonds in which it specializes.
Note: The data relied upon to generate this figure was TRACE Data provided by FINRA's TRACE System.

Figure 3 plots the cumulative share of dealers (y-axis) for which at $x\%$ of their total volume or less was generated in trading bonds they specialize in. We see that for more than half of the dealer trade in the bonds they specilize in accounts for at least 70% of their trade volume. This contrasts with what would be expected based on dealers' incentive to diversify in order to reduce risk.

Histogram of Dealer Share of Bond as pct. of its Share in Total Volume, 2019

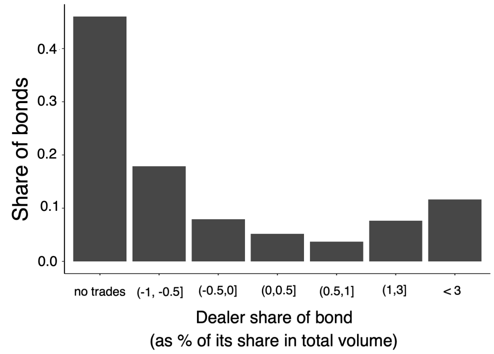

Figure 4: A dealer specializes in a bond, trades it sporadically, or avoids trading it altogether.
Note: The data relied upon to generate this figure was TRACE Data provided by FINRA's TRACE System.

To get further characterization of the distribution of bond trades of a dealer I observe the deviation of the share of dealer in trading a specific bond, d, denoted, compared to the share of the dealer in the entire market trade volume, $\bar{S}_{d,t}$:

$$\hat{\delta}_{b,d,t} = \frac{s_{b,d,t} - \bar{S}_{d,t}}{\bar{S}_{d,t}}$$

The distribution of $\hat{\delta}_{b,d,t}$ appears in Figure 4.

Two things pop to the eye from this distribution. First, it looks almost like a mirror image of a normal that would have emerged if dealers were equally likely to trade any security. Second, we see that each dealer completly avoids a substantial share of traded bonds. A typical large dealer avoids any trade in about 45% of the bonds in the market, and I found no single dealers who avoided less than 35%. The binary pattern of avoiding many bonds while trading very heavily on others is somewhat reminiscent of an entry cost setting.

Further characterization reveals that dealers tend to specilize in bonds of specific issuers and of issuers of specific industries. To see that more clearly, consider the following regression:

$$S_{d,b,t} = \beta_0 + \beta S_{d,i,t,-b} + \epsilon,$$

where $S_{d,b,t}$ is the share of dealer d in the total volume of bond b in year t, and $S_{d,i,t,-b}$ is the share of d in the volume of trade in all securities issued by dealer d besides security b. The results appear in Table 1:

	dealer share in trading the bond
(Intercept)	0.0123***
	(9.34×10^{-5})
dealer share issuer (but bond)	0.9780***
	(0.0019)
Observations	584,798
R^2	0.30679

Table 1: Trades in the year 2019
Note: The data relied upon to generate this figure was TRACE Data provided by FINRA's TRACE System.

A 1 bps increase in the share of dealer d in all securities of issuer i besides bond b presages a 0.98 increase in the share of that dealer in trading bond b. That is, if one would like to predict the percentage of trades of a dealer in a bond based on its share in other bonds issued by the same firm, the best guess would be to say that they are about the same. Also, the prediction explains a substantial part of the variance of the dealer share in trading bonds, as implied by the relatively higher R-squared of 0.3 [2].

In a similar fashion, I run the regression:

$$S_{d,i,t} = S_{d,j,-i} + \epsilon,$$

Where $S_{d,i,t}$ is the share of dealer d in the volume of all bonds issued b in year t, and $S_{d,j,t,-i}$ is the share of d in the volume of trade in all securities of all issuers from sector j besides i in year t [3]. The regression results appear in Table 2.

Again, there is a statistically significant positive correlation between the dealer share in trading firms in a particular industry and the likelihood that it trades the bonds of an issuer belonging to this industry. There is also a relatively high R-squared. Knowing only the

[2] In the appendix I show that while this is true a dealer also specilizes in specific bonds within each issuer, a fact that is apparent in the high prevalence of cases in which a dealer trades heavily on some bonds of the issuer while avoiding all trade in other bonds of that issuer.

[3] Issuers are assigned to sectors according to their 5-digits NAICS code from Mergent-FISD. The data includes issuers with 825 different NAICS codes

	dealer share issuer
(Intercept)	0.0134***
	(5.4×10^{-5})
dealer share industry (but issuer)	26.27***
	(0.0616)
Observations	670,459
R^2	0.21346

Table 2: Trades in the year 2019.
Note: The data relied upon to generate this figure was TRACE Data provided by FINRA's TRACE System.

dealer's share in trading, other issuers in the industry explain much of the variance in the data.

Dealers' tendency to specilize within specific issuers and industries imply a role for information. Economies of scope. Explain it in great detail... (finish writing this important paragraph).

Next paragraph: adverse selection mechanism. Quote: Easley and O'hara (1987) and Chalamandaris and Vlachogiannakis (2020) indicate that dealers themselves are subject to adverse selection, and they mitigate their losses by charging higher spreads in trades in which they might have an information disadvantage. Thus, if some dealers are better informed about a specific security, we would expect that they would be able to offer better prices and win a larger share of the order flow.

An immediate implication of such logic is that the dealers that dominate the order flow in a specific bond will charge lower spreads for trading it. This pattern indeed appears in the data, providing further support to the claim that concentration is the result of the advantage of informed vs. non-informed dealers. To see that, I run a regression that compares the markups of prominent vs. non-prominent dealers on trades conducted at the same bond, at the same volume, on the same day:

$$\text{spread} = \beta \text{dealer prominence}_{t-1} + \text{bond} * \text{trade size} * \text{date} + \text{dealer}$$

Where *dealer prominence* is a categorical variable that is assigned with the value "Non-active"

trade type	C2D		D2C	
Model:	(1)	(2)	(3)	(4)
Active	-0.2227 (0.5272)	-1.178** (0.5568)	2.218*** (0.3878)	-0.4710 (0.3933)
Prominent	-11.58*** (0.5805)	-3.841*** (0.6147)	-8.617*** (0.4351)	-2.611*** (0.4511)
bond - trade size - date	Yes	Yes	Yes	Yes
dealer		Yes		Yes
Observations	10,702,378	10,702,378	12,097,754	12,097,754

Table 3: Dealer prominence and spreads; All principal trades in the years 2006 - 2020

Note: The data relied upon to generate this figure was TRACE Data provided by FINRA's TRACE System.

if the dealer traded the bond less than five times in principal capacity, "Active", if the dealer traded it more than five times in principal capacity but accounts for less than 10% of total trade volume, and "Prominent" if the dealer traded the bond at least five times and accounts for more than 10% of total trade in the bond. I use the dealer prominence from the previous year to avoid bias due to reverse causality. The *trade size* variable categorizes trades into volume bins of $> \$100,000$, $\$100,000 - \$500,000$, $\$500,000 - \$1,000,000$, $\$1,000,000 - \$5,000,000$, and $\$ > 5,000,000$. The regression is applied to all principal trades occurring in the years 2006-2020. The results appear in table 3

What we can see is that dealer prominence is indeed associated with lower spreads. The differences are sizeable. For instance, we see that when a dealer who is prominent in the market for a specific bond purchases it from a customer, he charges a spread that is 12 bps lower than that charged by a non-active dealer. As spreads typically oscillate in a band of 15-30 bps, this is a remarkably substantial difference. When we add controls for dealer fixed effect, the difference is diminished to 3.84 bps. We see a similar pattern when a dealer sells to a customer and when comparing active and non-active dealers (although there the results are more ambiguous).

Lastly, I explore which bond attribute predict concentration. For that purpose. Table 4 shows the results of the regression model

$$HHI_{b,t} = X_{b,t}\beta + \epsilon$$

, where $X_{b,t}$ is a set of bond attributes in year t. These include the mean rating given to the bond according to Mergent FISD, the coupon rate, year to maturity, the age of the bond

Dependent Variable:	bond-level HHI			
Model:	(1)	(2)	(3)	(4)
Variables				
rating	-0.0008	-0.0045***	0.0108**	0.0082**
	(0.0021)	(0.0007)	(0.0026)	(0.0016)
coupon rate	0.0051	0.0080**	0.0077**	0.0079***
	(0.0038)	(0.0018)	(0.0015)	(0.0010)
non-standard coupon frequency	0.0650***	-0.0074	-0.0447*	-0.0423*
	(0.0070)	(0.0257)	(0.0179)	(0.0150)
rule 144a	0.0459***	0.0464***	0.0608***	0.0353***
	(0.0063)	(0.0052)	(0.0056)	(0.0043)
callable	0.0565***	-0.0356	-0.0205	-0.0213
	(0.0050)	(0.0220)	(0.0364)	(0.0333)
time to maturity	0.0007	0.0005*	0.0003	0.0003
	(0.0003)	(0.0002)	(0.0003)	(0.0003)
time since offering	0.0044***	0.0016	0.0045**	0.0029**
	(0.0006)	(0.0010)	(0.0009)	(0.0008)
issue size: 0-100m		0.1501**		0.1095***
		(0.0271)		(0.0143)
issue size: 100m-500m		0.1007***		0.0714***
		(0.0086)		(0.0047)
issue size: 500m-1t		0.0379***		0.0275***
		(0.0025)		(0.0044)
Fixed-effects				
industry	Yes	Yes	Yes	Yes
issuer			Yes	Yes
Fit statistics				
Observations	460,279	460,279	460,279	460,279
R^2	0.08608	0.21349	0.54168	0.56487
Within R^2	0.05716	0.18861	0.04507	0.09338

Clustered (industry) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 4: Regression - attributes of bonds traded in concentrated markets.
Note: The data relied upon to generate this figure was TRACE Data provided by FINRA's TRACE System.

(years since it was offered), and a categorical variable for the amount outstanding. Indicator variables for a bond that pays a coupon in a non-standard frequency, a bond that falls within the ambit of rule 144a, and a callable bond are also included. Last, industry group fixed effects and issuer fixed effects in some of the models are considered.

Two things about this table are noteworthy. First, is that low amount outstanding is the strongest predictor of a bond's concentration, apparent in the dramatic rise of R-square from 0.08 in its absence to 0.21 when it is included. This is consistent with an entry cost narrative in which larger markets (higher amount outstanding) allows more players to enter before competition erods profit to the extent. Second is that amount outstanding appears as the only variable with substantial explanatory power. That is, besides amount outstanding it seems that bonds at varying concentration level do not exhibit persistent differences from each other.

4 Concentration and Response to Systemic Distress

In this section, I explore the connection between concentration and deteriorating trdaing conditions during a crisis. I begin by demonstrating that dealer charge higher profit margins during a crisis. Then, I proceed to show that the rise in profit margins is larger for bonds that are traded in a more concentrated setting (higher HHI).

Table 5 presents the results of a regression that compares the prices in interdealer (D2D) trades to those of customer–dealer trades of the same bond on the same day and at about the same size. The goal is to isolate the customer–dealer wedge and how it changes in crises (see the table caption for specification details).

The sample covers the Great Recession (July 2007–May 2009) with a pre-period starting in January 2006, and the COVID-19 turmoil (March 5–April 10, 2020) with a pre-period starting in January 2019. I restrict to wholesale principal trades (volume ¿ $100k). I estimate the wedge separately for customer sells (C2D vs. D2D) and customer buys (D2C vs. D2D).

Results (Table 5) show a sizable customer–dealer gap in normal times that widens sharply in crises. Customers receive about 26 bps less than dealers in normal times; the discount grows by roughly 17–18 bps in crises (44 bps total, a 65% increase). I get similar results for customer buying from dealers. These patterns persist when adding dealer×date fixed effects, ruling out dealer-composition or time-varying dealer-level shocks as explanations.

I interpet these result to mean that crisis-time widening primarily reflects higher markups on customer trades rather than higher intermediation costs. If costs rose symmetrically, D2D and customer trades would move in tandem; instead, the customer–dealer wedge expands.

Next, I turn to study cross variance differences in dealers' markup response to crisis between bonds with varying levels of concentration. Based on the intuition that was just specified, I measure dealers' rents when purchasing securities from customers as the gap between the interdealer vs. customer-to-dealer price. More specifically, I define:

Dependent Variable:	price			
Trade Type:	C2D	D2C	C2D	D2C
Model:	(1)	(2)	(3)	(4)
Variables				
D2D	0.2603***	-0.2663***	0.2346***	-0.1883***
	(0.0065)	(0.0014)	(0.0031)	(0.0032)
D2D × Crisis	0.1734***	-0.1663***	0.1810***	-0.1506***
	(0.0102)	(0.0123)	(0.0071)	(0.0254)
Fixed-effects				
Bond × Date × trade_size	Yes	Yes	Yes	Yes
Dealer × Date			Yes	Yes
Fit statistics				
Observations	6,981,016	7,966,969	6,981,016	7,966,969
R^2	0.98731	0.98698	0.99154	0.99012
Within R^2	0.00128	0.00270	0.00132	0.00099

Clustered (cusip_id-trd_exctn_dt-t_size) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 5: Regression of trade price on indicators for interdealer trades (D2D) and their interaction with a crisis dummy, with bond×date×trade-size fixed effects in all columns and dealer×date fixed effects in cols. (3)–(4). The dependent variable is the trade price; coefficients are in price points per $100 par value (interpretable as bps). "C2D" compares customer sells to D2D; "D2C" compares customer buys to D2D. Crises are the Great Recession (Jul 2007–May 2009) and COVID-19 turmoil (Mar 5–Apr 10, 2020); pre-periods start Jan 2006 and Jan 2019, respectively. Sample restricted to principal trades with volume ¿$100k. Standard errors clustered by (cusip×date×size). The crisis interaction captures the incremental widening of the customer–dealer wedge in distress relative to normal times.
Note: The data relied upon to generate this table was TRACE Data provided by FINRA's TRACE System.

$$textmarkup = \ln\left(\frac{\text{trade price}}{\text{interdealer price}}\right) \tag{2}$$

Where the interdealer price refers to the price of the bond at the most recent interdelaer trade. The measure is often used in the literature to gauge the bid-ask spread (see, for instance, O'Hara and Zhou (2021), Choi et al. (2021)). Dealers typically buy at lower prices and sell at higher prices than customers, so the interdealer price lies between the customer bid and ask prices. Interpreting the interdealer price as close to fundamental value, the markup reflects the cost of trade embedded in the bid–ask spread.

I apply a transaction-level regression model of the form:

$$\begin{aligned}
Spread_{i,d,b,t} = \alpha_0 + \beta_1 * HHI_{b,t-1} + \beta_2 * HHI_{b,t-1} * \mathbb{I}\{Crisis\} \\
\gamma * X_{b,t} + \eta_d + \xi_b + \nu_i + \text{trade_date}+ \\
\eta_d * \text{trade_date} + \xi_b * \text{trade_date} + \nu_i * \text{trade_date}+ \\
\lambda_b + \lambda_b * \text{trade_date} \quad (3)
\end{aligned}$$

In the LHS of the regression, we have the spread of trade i done by dealer d in bond b at time t. Our main object of interest is β_2 - the coefficient on the interaction term between the concentration level of the bond and the trade being conducted during a crisis. Note that the regression has a dif-in-dif flavor to it, with the bond HHI measuring the size of the treatment and the crisis indicator being the post-treatment dummy. The value of β_2 determines to which extent does the treatment, that is, the HHI, presages a change in the outcome, which is the spread. To diminish bias due to changes in fundamental prices over time, I weigh trade by the inverse of the distance in time to the D2D trade that determines the benchmark price for calculating the spreads.

The regression includes an elaborate set of controls. First, the vector $X_{b,t}$ is a vector of bond attributes that include: age, time to maturity, square root of amount outstanding, the issuer industry, and more (for the full list, see Table 9 in the appendix). Alongside, I include fixed effects for the dealer's identity, ξ_d, the bond rating, ξ_b, the trade size, ν_i, and the bond's liquidity. I transform the trade size to a categorical variable by dividing it into the following bins: [$100-$500), [$500k-$1m), [$1m - $5m), and above $5m. I measure liquidity by the number of days in which the bond was not traded in the previous year - a common measure in the literature. I use only trades in which dealers trade bonds with customers, to avoid a mechanical correlation between this measure and the concentration measure, stemming from the fact that markets with more dealers will have a higher frequency of dealer-to-dealer trades (Below, I show that my results also hold with an alternative liquidity measure that incorporates these dealer-to-dealer trades into the regression). I divide the measure into bins that correspond to five percentile ranges of the liquidity variable.

Further, the regression includes an interaction term of each of the fixed effects with a date categorical variable. If I would have used an interaction term of each fixed effect with the crisis indicator, it would have captured the expected change in the spread of each trade given the attribute represented by the fixed effect. For instance, a dealer-crisis fixed effect would have captured the average addition of each specific dealer to the spreads it charges in crisis times. The interaction of a fixed effect with the date variable does even more. Continuing with the same example, the interaction of a dealer and date fixed effects not only (indirectly) embeds the changes in the spreads dealers charge during a crisis, it also controls for changes in these spreads throughout different phases of the crisis period. To see that, assume that less liquid bonds are traded in more concentrated markets and that they are typically traded only deep into the crisis when spreads are higher. In that case, the interaction term of date and liquidity will capture the expected change in the spread of a bond with a certain liquidity level, given that it was traded at a specific time in the crisis. That, in turn, will prevent these changes from contaminating the estimate of β_2.

In table 6, I report the results of applying the regression model to the COVID-19 crisis and the period proceeding it (columns 1-3) and to the 2007-2009 crisis and the period proceeding it (columns 4-6) [4]. In each, I run the analysis on the full sample, only on trades in which a customer sells to a dealer (C2D) and only on trades in which a dealer sells to a customer (D2C). What we can see is that in both crises period, higher concentration was correlated with a substantial increase in spreads in trades in which a customer sells to a dealer. In the great recession, a 10 bps increase in HHI was correlated with a 1.6 bps higher "jump" in the spreads in customer-to-dealer trades in a crisis. In the COVID-19 crisis it was correlated with a staggering 9 bps rise in the gap between spreads pre-crisis and during the crisis period. In both cases, the result is statistically significant. This pattern is exactly what we predicted if dealers indeed exploit the distress of customers in dire need of liquidity to charge higher markup for inter-mediation. Interestingly, for cases in which a dealer sells to a customer, we see the opposite effect - higher concentration presages a milder increase in the spreads in times of systemic distress. In absolute size, the effect is about half the size of what we see with customer-to-dealer trade. In the next few pages, as we turn to take a closer

[4] For full results that also report the coefficients on control variables, see table 9 in the appendix

look at the regression analysis, we see that this correlation, while statistically significant in this specification, is not robust and is likely to be explained away as a spurious correlation originating from limitations of the spread measure.

Dependent Variable:	spread					
		COVID-19 Crisis			GRC	
Population:	All	C2D	D2C	All	C2D	D2C
Variables						
HHI	5.7*** (1.4)	13.7*** (1.1)	0.64 (0.92)	-0.01 (5.9)	9.3** (4.1)	-0.21 (3.2)
HHI × crisis indicator	27.6*** (8.4)	92.0*** (9.8)	-43.2*** (9.6)	2.0 (8.4)	16.0*** (5.7)	-8.4* (4.3)
Fixed-effects						
rating	Yes	Yes	Yes	Yes	Yes	Yes
trade size	Yes	Yes	Yes	Yes	Yes	Yes
dealer	Yes	Yes	Yes	Yes	Yes	Yes
dealer-date	Yes	Yes	Yes	Yes	Yes	Yes
date	Yes	Yes	Yes	Yes	Yes	Yes
# days traded (prv. year)	Yes	Yes	Yes	Yes	Yes	Yes
# days traded (prv. year)-date	Yes	Yes	Yes	Yes	Yes	Yes
rating-date	Yes	Yes	Yes	Yes	Yes	Yes
trade size-date	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	1,375,793	656,133	719,660	621,479	271,191	350,288
R^2	0.11938	0.25548	0.21531	0.19310	0.36171	0.36307
Within R^2	0.00693	0.00936	0.01212	0.00485	0.00735	0.00997

Clustered (rating) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 6: Results from applying the standard model (eq 3) to the Covid-19 crisis and the period proceeding it and to the GRC and the period proceeding it; Abbreviated. Note: The data relied upon to generate this table was TRACE Data provided by FINRA's TRACE System

Here, I present a set of results attained from regression analysis. The analysis does not meet the gold standard of studying causality in economics. That is, the assignment of the "treatment" (concentration) is not random. Therefore, I cannot negate the possibility that some third element that determines bond-level concentration also underlies its responsiveness to systemic distress. However, the regression analysis allows me to refute well-specified alternative explanations of the correlation by adding controls for the most likely confounders like bond liquidity, the dealer expected holding period, and the dealer's identity. Further robustness checks of the relation between concentration and rising spreads during a crisis, as well documentation of stylzed facts showing a stronger decline of volume in markets with higher dealer concentration are available at the appendix.

5 Model

Enviornment: A unit mass of customers (sellers) each holds one unit of a bond B and may sell it for a numerire good (money) to a set of dealers. There are $n \in \mathbb{N}$ *informed* dealers and a competitive fringe of *uninformed* dealers. All players are risk neutral and maximize expected payoff.

Asset Payoffs and Information: The bond's value v is high, $v_h > 0$, with probability $q \in (0,1)$, and low, $v_l := \rho v_h$, with probability $1-q$, where $0 < \rho < 1$. As is standard in asymmetric information settings, the customer (bond holder) observes the true quality; informed dealers who specialize in this bond observe v as well, while the uninformed fringe does not.

Liquidity Shocks and Customer Behavior: Customer i is willing to sell at any price $p \geq R(v, \delta_i) := v - \delta_i$. There are two shock levels: a regular shock $\delta_r > 0$ with probability $1-\xi$ and a severe shock $\delta_s > \delta_r$ with probability $\xi \in (0,1)$.

Assumption 1 (Ordering)**.** *$v_l < v_h - \delta_s < v_h - \delta_r < v_h$. Set $R_r := v_h - \delta_r$ and $R_s := v_h - \delta_s$.*

Let $s(B)$ denote the share of customers holding a high-quality bond willing to sell it for a price of B. We can write:

$$s(B) = \begin{cases} 1, & B \geq R_r, \\ \xi, & R_s \leq B < R_r, \\ 0, & B < R_s, \end{cases}$$

Trading Protocol: A customer solicits quotes. Each informed dealer is available with probability $1-\pi$ and, if available, submits a bid (purchase price). The probability of failing to bid, π represents limitations on trade due to capacity constraints or search frictions. The uninformed fringe is a measure-one competitive sector that posts a single price, B^U and commits to fill any individual seller at that price. By the law of large numbers, an individual seller (who is atomistic) treats this outside option as surely available. This assumption reflects the notion that a customer can always find a dealer that will buy a security for a sufficient discount, that is, a discount that compensates for buying a security that the dealer is not familiar with. The customer accepts the highest bid above her reservation value. Ties are randomly broken.

Ordering Assumption: I assume, WLG, that $v_l < v_h - \delta_s$

5.1 Strategies and Equilibrium

Let $\Omega = \{v_h, \rho, q, \pi, \delta_r, \delta_s, \xi, n\}$. The fringe posts $B^U \in \mathbb{R}_+$. Informed dealers use a CDF $F(\cdot; \Omega)$ over bids when $v = v_h$ and (as shown below) do not bid when $v = v_l$. Denote by $\mu(B)$ the probability assigned by an uninformed dealer that a bond it purchased for a price of B is of high quality.

Definition 5.0.1 (Equilibrium). *A symmetric equilibrium consists of* $(B^U, F, \mu(B))$ *such that:*

(U0) The competetive fringe breaks-even conditional on winning the auction:

$$B^U = \mu(B^U)v_h + (1 - \mu(B^U))v_l$$

If multiple bids allow it to break even, the heighest among them will be choosen [5]*.*

(I) (Informed optimality) When $v = v_h$*, bids in the support of* F *maximize expected profit; when* $v = v_l$*, informed do not bid (WLOG).*

(C) (Consistency) $\mu(\cdot)$ *is derived from equilibrium strategies via Bayes' rule.*

[5] Condition (1) fixes the uninformed strategy rather than deriving it from a no-profitable-deviation condition. The online appendix provides microfoundations showing that, for any fixed $n \geq 2$, this reduced form arises as the appropriate limit of the full game. Specifically, the simplified equilibrium here is the $(m \to \infty,\ \kappa \downarrow 0)$ limit of a model with n informed dealers and m potential uninformed entrants who face a vanishing per-quote cost $\kappa > 0$ and a small peer-relative penalty $\phi > 0$.

6 Solving the Model

6.1 Preliminaries

Lemma 6.1. *The fringe bids* $B^U \geq v_l$

Proof. For any bid $B' < v_l$:

$$\mu(B^U)v_h + (1-\mu(B^U))v_l - B^U = \mu(B^U)(v_h - B^U) + (1-\mu(B^U))(v_l - B^U) > 0$$

Violating the break-even condition. □

Note that since $B^U \geq v_l$, an informed dealer cannot generate a profit on trading the low-quality bond. It is therefore without loss of generality to assume, as I do here, that informed dealers do not bid when $v = v_l$.

Lemma 6.2. *When the security is of high quality, the informed bids are always strictly higher than* $B^{U^*}(n)$.

Proof. Regardless of the strategy of the informed, there is a probability of at least $(1-\pi^n) * (1-q_h)$ that a bond bought by the uninformed is of low quality. Hence $B^U < v_h$. If the informed bids below B^U it cannot win the auction and he has a payoff of zero, while if he bids in the interval (B^U, v_h) he attains a positive payoff with probability $[\pi + (1-\pi)F(B)]^n > \pi^{n-1} > 0$. □

Thus, an informed dealers will win the auction as long as at least one informed dealer participates in it, which happens with a probability of $(1-\pi^n)$. We immideatly recieve the general pattern seen in the data of a concentrated market dominated by a few dealers that charge a lower spread (higher price) for trading the bond.

Lemma 6.3 (Posterior on fringe purchases)**.** *The probability that an asset sold to the* *competetive fringe for B^U is of high quality is:*

$$\mu_n(B^U) = \Pr(v = v_h \mid \textit{sold to fringe at } B^U) = \frac{q\,\pi^n\, s(B^U)}{q\,\pi^n\, s(B^U) + (1-q)}.$$

Proof. A high quality security will be sold to the fringe for B^U if: (i) no informed players places a bid, which happens with probability π^n (see Lemma 6.2), and (ii) the seller is willing to accept this bid, which happens with probability $s(B^U)$. In contrast, for a low quality security the informed does not bid and since $B^U \geq v_l$ all customers are willing to sell. Using Bayes Rule:

$$\mu_n(B^U) = \Pr(v = v_h \mid \text{sold to fringe at } B^U) = \frac{Pr(\text{sold to fringe for } B^U | v = v_h)}{Pr(\text{sold to fringe for } B^U)} Pr(v = v_h) = \frac{q\pi^n s(B^U)}{q\pi^n s(B^U) + (1-q)} \quad (4)$$

□

6.2 Regime Switching and Adverse Selection

6.2.1 Equilibrium With Mild Adverse Selection

First, let us define a parameteric condition for adverse selection:

Definition 6.3.1 (Mild Adverse Selection)**.** *We will say that the market has mild adverse selection when:*

$$(1-\rho)\frac{(1-q)}{q\pi^n + (1-q)} < \frac{\delta_r}{v_h} \quad (5)$$

Else, we will say that there is substantial adverse selection

The left-hand side is the percentage discount the fringe needs to break even in the "full-participation" region $s(B^U) = 1$: it is the quality gap $(1-\rho)$ scaled by the posterior chance of a lemon conditional on a fringe sale. The right-hand side is the size of the "regular" liquidity motive as a share of value. Mild adverse selection means the liquidity motive is strong enough to keep the fringe active at a price accepted by all customers, which is shown more formally in the following lemma:

Theorem 6.4 (Uninformed Liquidity Provision With Mild Adverse Selection)**.** *Let:*

$$B_1 := v_l + \frac{q\pi^n}{q\pi^n + (1-q)}(v_h - v_l) > v_h - \delta_r$$

With mild adverse selection (condition 6.3.1) the competative fringe bids $B^U = B_1$. Else, $B^U < v_h - \delta_r$

Proof. Using $v_h(1-\rho) = v_h - v_l$ we can rewrite Eq. 5 as:

$$v_h - \delta_r < \frac{q\pi^n}{q\pi^n + (1-q)} v_h + \frac{(1-q)}{q\pi^n + (1-q)} = B_1$$

Since $B_1 > v_h - \delta_r$, the share of sellers willing to sell the high quality bond at that price is $s(B_1) = 1$. Therefore, $\mu(B_1) = \frac{q\pi^n}{q\pi^n + 1 - q}$, and we find that:

$$B_1 = \mu(B_1)v_h + (1 - \mu(B_1))v_l$$

as required by the break-even condition. By lemma 6.2 for any $B' > B_1$ the probability that the uninformed wins the high quality bond is π^n and its payoff is:

$$\mu(B')v_h + (1-\mu(B'))v_l - B' = \mu(B_1)v_h + (1-\mu(B_1))v_l - B_1 - (B' - B_1) = 0 - (B' - B_1) < 0$$

meaning that B_1 is the heighest price for which the uninformed can breakeven, as desired. □

The take-away from Theorem 6.4 is that as long as adverse selection is not too dire, the uninformed fringe provides a backstop and can meet the liquidity needs of the entire market. That is, they set a price that is high enough to compensate non-distressed customers for losing the security. Furthermore, notice that in this scenerio all customers get to trade regardless of the tightness of dealers capacity constraints, π. That is, search frictions or limited availability of some dealers to due tigher funding constraints have no affect on trade volume as long as the asset composition is such that dealers are willing to buy securities they are not familiar with for a modest discount. In this scenerio, any dealer can meet the liquidity needs of a potential customer. While some dealers pay more, and hence get a larger share of the market, overall the market leads to all transactions eventually occuring.

Now, let us turn to characterize the behavior of the informed in this scenerio:

With mild adverse selection (Eq. 5) the informed CDF, F will be an atomless function with support $[B^U, \bar{b}_0]$ given by:

$$F(b) = \frac{\pi}{1-\pi}\left[\left(\frac{v_h - B^U}{v_h - \bar{b}}\right)^{\frac{1}{n-1}} - 1\right], \quad \bar{b} = v_h - (v_h - B^U)\,\pi^{n-1}.$$

Proof. From the perpsective of the informed, the presence of the uninformed is equivalent to having customers' reservation value rise from their subjecive valuation of the bond, $v_h - \delta_i$, to their outside option of selling it to an uninformed for $B^U > v_h - \delta_i, i \in \{r, s\}$. Thus, the setting is identical to the canonical Varian (1980) model of sales we can show that the in equilibrium the function $F()$ will be atomless and implicitly defined by:

$$[\pi + (1-\pi)F(B)]^{n-1}(v_h - B) = \pi^{n-1}(v_h - B^U) \tag{6}$$

For any $B \in (B^U, \bar{b}]$, where $\bar{b} = v_h - (v_h - B^U)\,\pi^{n-1}$.

□

Following Varian (1980) we can specify the strategy of the informed based on

Corollary 6.4.1 (No Transmission of Liquidity Shocks Without Adverse Selection)**.** *With mild adverse selection the equilibrium allocation and the distribution of prices is identical for all values of* (ξ, δ_s) *and any value of* δ_r *that does not violate condition 5.*

Proof. The corollary is an immideate result of the fact that we can fully derive and characterize the strategies informed (Lemma 6.2.1) and uninformed (Theorem 6.4) without referring to any of these parameters. □

The implication of the corollary is that with low levels of adverse selection distress of customers in OTC markets does not get transmitted to prices or volume. This is because informed dealers cannot exploit the distress to submit lower bids that solely target customers who got hit by severe shocks. Such bids will be turned down in favor of better offers given by the uninformed. Thus, we find that substantial adverse selection is a pre-condition for systemic distress to incentivize dealers to exercise their market power more aggresivly. We shall see this more clearly next as we turn to examine the behavior of the model when adverse selection leads the uninfortmed to withdraw from the market:

Theorem 6.5. *Assume substantial adverse selection (condition 6.3.1 doest no hold) and:*

$$v_l + \frac{\xi q \pi^n}{\xi q \pi^n + 1 - q}(v_h - v_l) < v_h - \delta_s$$

Then, the uninformed will withdraw from trading the high quality bond and submit a bid of $B^u = v_l$. *The informed bid will depend on the level of adverse selection, where: If* $\xi > \frac{\delta_r}{(v_h - \bar{R}^s)\pi^{n-1}}$ *informed dealers bid below* $v_h - \delta_s$ *and trade only with distressed customers. If* $\xi < \frac{\delta_r}{(v_h - \bar{R}^s)}$, *their they bid above* $v_h - \delta_r$ *and their bids are accepted by both distressed and non-distressed sellers. If* $\xi \in (\frac{\delta_r}{(v_h - \bar{R}^s)}, \frac{\delta_r}{(v_h - \bar{R}^s)\pi^{n-1}})$ *the support of* F *is divided into two segments, one in the range* $[v_h - \delta_s, x], x < v_h - \delta_r$, *that consists of bids that are accepted only by distressed players, and the other in the range* $[v_h - \delta_r, y], y < v_h$, *consisting of bids accepeted by both distressed and non-distressed.*

As we can see, once the adverse selection is severe enough to lead the uninformed to withdraw from the market we will generally see a rise in bid-ask spreads, and we will witness a transmission of distress among the customers into market prices and volume. Also, notice that in the case that some bids target the distress and some target the non-distress changes in the level of competition among the informed, namely in n, will have a sizeable impact on the average spread that they charge. This is because in these cases the weaker competition results in higher likelihood of submitting bids in the lower range of F, that is bids that target only the distress. As we shall see in the calibration, this property of the model allows it to explain hte sizeable differences in bid-ask spreads between markets for bonds with varying levels of competition during a crisis. The exact level of these spreads is characterized in the following theorem:

Theorem 6.6. *([Calculating the average spread) If informed dealers submit bids that are higher than $v_h - \delta_r$ and some that are low, the average spread they charge customers will be:*

$$\hat{S}^i(n) = \frac{n(1-\pi)\pi^{n-1}(v_h - \bar{R}^s)}{V^i(n)}$$

Where $V_i(n)$, the total volume traded by informed players, is given by:

$$V_i(n) = (1-\pi^n)[1-(1-\xi)\sum_{k=1}^{n}\binom{n}{k}\pi^{n-k}(1-\pi)^k(F(v_h-\delta))^k]$$

If all the bids submitted by the informed exceed $v_h - \delta_r$, then:

$$\hat{S}^i(n) = \frac{n(1-\pi)\pi^{n-1}(v_h - \bar{R}^r)}{1-\pi^n}$$

And if all of these bids fall short of $v_h - \delta_r$, the average spread will be:

$$\hat{S}^i(n) = \frac{n(1-\pi)\pi^{n-1}(v_h - \bar{R}^s)}{1-\pi^n}$$

7 Calibration

The calibration tests whether the mechanism can match the levels and cross-sectional dispersion of spreads (and the associated volume changes) across markets with different concentration. I model two states, normal g and crisis c. A crisis changes the composition of traded assets (v_l^i, q_h^i), tightens dealer capital constraints π^i, and raises liquidity demand through a higher share of distressed customers ξ^i $(i \in \{g, c\})$. I normalize $v_h^i \equiv 1$ and I am left with ten parameters $\{v_l^g, v_l^c, q_h^g, q_h^c, \pi^g, \pi^c, \xi^g, \xi^c, \delta_r, \delta_s\}$.

To reduce selection concerns, I calibrate to customer-to-dealer *sales* of "BBB–" bonds with par \$1–\$5 million, executed by the top 50 dealers in principal capacity. Following Kargar et al. (2021), the crisis window is March 5–April 10, 2020; "normal" is Jan. 1, 2019–March 4, 2020. I pin down two normal-time primitives outside the optimization. First, I set the seller holding cost for BBB- rated bonds to $\delta_r = 0.75\%$, the midpoint between the Ba (83 bps) and Baa (67 bps) estimates in Chen et al. (2018). Second, I set the share of distressed customers in normal times to $\xi^g = 0$; As I show below, thbe results are not sensitive to this size choice.

I identify asset composition from re-rating dynamics in Mergent FISD. I interpret q_h^i as the share of "typical" (higher-quality) bonds within a market; the complement $1 - q_h^i$ is the share of appear the same but are in face more risky. Assuming random auditing, $1 - q_h^i$ equals the downgrade probability conditional on a re-rating (upgrade, downgrade, or re-affirmation). Pre-crisis, the conditional downgrade rate for BBB– is 13%, so $q_h^g = 0.87$; in the crisis it rises to 18%, so $q_h^c = 0.82$. I set the low state value v_l^i to the expected value conditional on downgrade, measured with inter-dealer prices (dealers face fewer frictions), restricting to small trades ($<$ \$10,000) to limit inventory-cost effects. Denote by $\nu^P_{\text{dngrd,BBB-}}$ the expected inter-dealer price of a downgraded BBB– bond in period $P \in \{\text{pre}, \text{crisis}\}$, and by $\nu^P_{\text{BBB-}}$ the contemporaneous BBB– price. With $v_h^i \equiv 1$, I obtain

$$v_l^g = \frac{\nu^{\text{pre}}_{\text{dngrd,BBB-}}}{\nu^{\text{pre}}_{\text{BBB-}}} = 0.997, \qquad v_l^c = \frac{\nu^{\text{crisis}}_{\text{dngrd,BBB-}}}{\nu^{\text{crisis}}_{\text{BBB-}}} = 0.89.$$

The sharp decline in v_l during the crisis reflects a general widening of inter-dealer price gaps across ratings, consistent with a higher cost of bearing idiosyncratic risk; in the model this interacts with concentration to amplify spreads in crises.

I map concentration to the number of informed dealers $n \in \{1, 2, 3\}$ using three HHI bins: 0.3–0.4 $\Rightarrow n = 3$, 0.4–0.6 $\Rightarrow n = 2$, and $> 0.6 \Rightarrow n = 1$. For each bin and period, I compute a weighted mean customer-to-dealer spread using the O'Hara–Zhou benchmark (percentage deviation from the most recent inter-dealer price). To limit measurement error, I keep only trades whose reference inter-dealer print occurred 1 hour–2 weeks earlier (to avoid agency misclassification and staleness), form bond–period weighted means (weights are the inverse time gap to the reference print), winsorize these bond–period means at the 10th/90th percentiles, and then average across bonds using trade-count weights.[6] The resulting moments (with concurrent volume changes for validation) are:

HHI	Spreads (pre-crisis)	Spreads (crisis)	Volume Change
> 0.6	24.41	169.30	-0.71
0.4–0.6	24.25	113.98	-0.33
0.3–0.4	15.37	98.80	-0.15

Table 7: Weighted mean spreads by HHI (pre-crisis vs. crisis) and associated volume changes.

I use these six spread moments to estimate the remaining parameters $\{\delta_s, \xi^c, \pi^g, \pi^c\}$ by minimizing squared percentage errors,

$$\min_{\delta_s, \xi^c, \pi^g, \pi^c} \sum_{i \in \{g,c\}} \sum_{n \in \{1,2,3\}} \left(\frac{\hat{\bar{S}}_n^i - \bar{S}_n^i}{\bar{S}_n^i} \right)^2, \tag{7}$$

where $\bar{S}_n^i$ denotes the data moment and $\hat{\bar{S}}_n^i$ its model counterpart; I impose $\pi^c > \pi^g$ to reflect tighter dealer constraints in distress. Volume changes are not targeted and serve as out-of-sample validation.

Because these parameters interact non-monotonically (e.g., raising π both strengthens informed dealers' market power and can induce more aggressive bidding by the uninformed), the

[6] See Section 4 and O'Hara and Zhou (2021) for the spread construction. The 1-hour lower bound excludes likely agency pairs; the 2-week upper bound limits stale references.

objective is non-convex. I therefore use a particle-swarm search. For each candidate vector I combine it with the primitives fixed above, recover $F(v_h - \bar{R}^r)$—the probability that informed bids attract only distressed customers—using the informed dealers' optimality condition (Eq. 6), compute implied spreads via Theorem 6.6, and evaluate (7). Implementation details are provided in the Appendix.

7.1 Calibration Results

The full list of model parameters appear in Table 8. In calibrating the model to replicate the behavior of spreads, I find that $\xi^c = 0.55$, that is, in a crisis, 55% of the sellers are distressed. Further, $\delta_s = 0.00165$, that is, those sellers are willing to sell the asset at a discount of 165 due to pressing liquidity needs. Note that this is about twice the decline in value that prompts regular sellers to sell, of 83 bps ($\delta_r = 0.83$). Alongside, the likelihood that a dealer fails to bid, π, is 0.35 in normal times, and 0.49 in a crisis. Hence, systemic distress raises this likelihood by 42%. Recalling that the likelihood embeds both higher holding costs and search frictions and that the latter are less affected by the crisis, these seem like reasonable estimates.

Variable	Value	Interpretation	Corresponding Moment/Source
q_h^g	0.87	Pr. that a bond is of high quality, normal times	Pr.(downgraded | rating updated) pre-crisis.
q_h^c	0.82	As above, crisis	As above, crisis
v_l^g	0.99	Value of a low quality bond, normal times	Expected change in the D2D price following a downgrade (pre-crisis)
v_l^c	0.89	As above, crisis	As above, (crisis)
δ_r	0.0083	Liquidity shock incurred by non-distressed customers	Chen et al. (2018)
δ_s	0.0165	Liquidity shock incurred by distressed customers	crisis spreads.
ξ^g	0	Share of distressed customers in normal times	(Unidentified).
ξ^c	0.55	As above, crisis	Change in volume
π^g	0.35	Prob. that the dealer does not submit a bid in normal times	Pre-crisis spreads.
π^c	0.49	As above, crisis	crisis spreads.

Table 8: Calibrated model parameters.
Note: The data relied upon to generate this figure was TRACE Data provided by FINRA's TRACE System.

In figure 5 I plot the spreads in normal times in the data (pre-crisis era) and in the model.

As we can see, the model does very well in replicating the data, both in terms of magnitude and shape. Specifically, both produce a substantial increase in spreads in the transition from a three-informed dealers market to a two-informed dealer market and more or less identical spreads in markets with two-informed dealers versus those with a single-informed dealer.

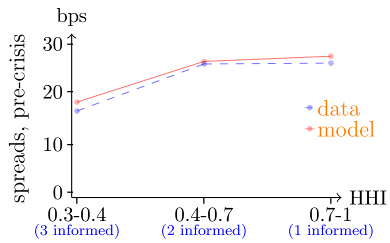

Figure 5: Spreads in the pre-crisis period: model vs. data,
Note: The data relied upon to generate this figure was TRACE Data provided by FINRA's TRACE System.

Irrespective of the variables we chose to fit the behavior of spreads, $\delta_s, \xi^c, \pi^g, \pi^c$, we find that v_l is higher than the value assigned to a high-quality bond by a non-distressed seller, $v_h - \delta_r$. Recall that uninformed dealers will always bid weakly above v_l, and hence will submit a bid that is sufficiently high to compensate any customer. That implies that the reservation value of sellers in this setting is not determined by their valuation of the bond, but rather by their outside option of selling it to an uninformed dealer. As a result, the distribution of sellers' liquidity shocks, embedded in δ_s, δ_r, and ξ^c has no impact on spreads in the calibrated model at regular times. In other words, the *shocks irrelevance condition*, presented in Theorem **??**, holds. This fact also means that the assumption that I made above, that $\xi^c = 0$, is benign - it has no implications for the behavior of the model.

Critically, among the four variables that we calibrated to fit the model to spreads in the data, $\delta_s, \xi^c, \pi^g, \pi^c$, the only one that has any relevance for its behavior in regular times is π^g - the probability that a dealer fails to bid. π^g shapes the spreads through two channels operating in opposite directions. First, alongside the asset composition, embedded in q_h^g, v_l^g, it pins down the bid of uninformed, $B^U(n)$. The higher is π^g, the weaker is the adverse selection, and the higher is $B^U(n)$. That, in turn, improves sellers' outside options and diminishes spreads. At the same time, an increase in π^g weakens competition between informed dealers, and by that, increases spreads.

What happens in the calibrated model is that the transition from two dealers to one lower the exposure of uninformed players to adverse selection and leads them to bid more aggressively. As a result, they pose greater competition to the informed player. That offsets the increase in spreads due to weakened competition among the informed dealers. In the transition from two informed dealers to one, the size of each force is about the same, so we witness a negligible

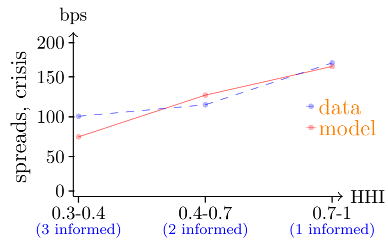

Figure 6: Spreads in a crisis period: data vs. model
Note: The data relied upon to generate this figure was TRACE Data provided by FINRA's TRACE System.

change in spreads. In this context, note that the variable π^g is calibrated to fit three different moments - spreads in normal times for markets with one, two, and three informed players. Given that this is the case, the good fit that the model attains cannot be taken for granted.

In figure 6, we see the behavior of spreads in crisis in the model and in the data.

In this case, the shocks irrelevance condition does not hold due to the sizeable differences in values between high and low-quality bonds embedded in $v_l^c = 0.89$. We attain an excellent fit for the data. That should not count for much of an achievement, as we match 3 variables, δ_s, ξ^c, π^c, to three moments characterizing spreads in that state. Specifically, we find that with $n = 1$, the informed dealers use their monopoly power to set the spreads to equal the reservation value of the distressed seller, $v_h - \delta_s$. The other two variables aim to replicate the spreads for markets with 2 or 3 informed players.

The calibration of the model of the behavior of spreads implies an explanation as to why spreads increase so dramatically in concentration in times of distress but change very mildly alongside HHI in the pre-crisis period. The reason lies in the substantial growth in the gap between the value (measured by inter-dealer price) between regular bonds and lemons, embedded in $v_l^c = 0.89$ and $v_l^g = 0.997$. In normal times, absent a large difference between v_h and v_l, the risk in purchasing an unfamiliar bond is not substantial enough to drive out uninformed dealers from submitting *relevant* bids, that is, bids that are high enough to answer the liquidity needs of all customers. Hence, customers always have the outside option of selling their assets at a reasonable price to *some* dealer. This outside option imposes limits on informed dealers' ability to exploit their market power and charge high spreads. Specifically, it prevents them from gaining any business by submitting low bids that only appeal to the distressed.

In other words, in the pre-crisis period, the adverse selection problem of the uninformed is much less dire. Hence, the uninformed can (and does) submit bids that are high enough to appeal to customers who hold a high-quality bond. The customer's outside option of attaining a reasonable deal when trading with the uninformed limits informed dealers' ability to exercise market power and bid low.

Now, I turn to compare the implications of the model for the behavior of volume change in response to the crisis to what we find in the data itself. Note that volume change, in contrast to spreads, was not a target in the calibration.

To allow for this comparison, I first need to create a volume change measure that applies to analogous objects in the model and in the data. The issue here is that while the model assumes that the measure of sellers, μ_s, is the same in the pre-crisis and the crisis period, in the data that need not (and probably is not) the case. Thus, to keep the two comparable, I define the data volume change in trades of bonds in markets with n informed players by:

$$\delta V(n) = V_{r,n} \alpha V_{c,n}$$

Where $V_{r,n}$ denotes the volume traded in such bonds in the pre-crisis period, $V_{c,n}$ the volume traded in those bonds in the crisis period, and $\alpha > 0$ being a multiplier used for adjustment.

One natural candidate to α would be the ratio between the length of the pre-crisis period and the crisis period. While this should improve the measure, However, it ignores the fact that during the crisis, the daily demand for liquidity is probably higher. Another alternative would be to use α so that the aggregate volume in both periods would be about the same. The problem with doing so is that aggregate volume is an endogenous variable and in fact, the variable we want to study. Thus, I set $\alpha > 0$ to be a positive number so that highly competitive markets, that is, those in which HHI < 0.3, experience no volume. This is consistent with the model, in which as n increases, one converges towards competitive pricing in which all demand for liquidity gets answered. I find that $\alpha = 7.5$.

In figure 7, I plot the $\delta V(n)$ for the data and for the calibrated model. As we can see, the model replicates the data with a very high level of precision. That occurs in spite of the fact that volume was not a target for the calibration.

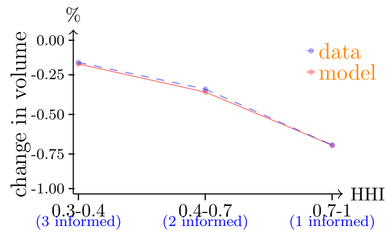

Figure 7: Volume response to the crisis: data vs. model
Note: The data relied upon to generate this figure was TRACE Data provided by FINRA's TRACE System.

A conservative interpretation of this result is that the differences in the response of volume to systemic distress across markets with varying levels of competition resemble what we would have expected to find if the forces that underlie them are indeed those that govern the model: (i) limited capacity of the informed dealers, and (ii) a strategical choice of dealers to submit bids that target only distressed sellers.

Granted, the co-movement of volume and spreads across markets with varying levels of competition is already baked into the model from the get-go. Yet, while the model structure might determine the shape, it cannot determine exact values. Hence, the success in replicating volume not only in its shape but also in absolute sizes is not, ex-ante guaranteed. Thus, it provides some evidence in favor of the theory that the model embeds.

Furthermore, note the sizeable differences in the response of volume across markets with varying levels of concentration. If the decline in volume indeed originates from concentration, as suggested here, even low concentration levels as HHI $\in [0.3, 0.4]$ lead to a 15% decline in trade volume, while higher levels are associated with an even greater decline. Recalling that 75% of the bonds have an HHI that is greater than 0.3, this can be taken to indicate that concentration has a sizeable contribution to the decline in trade volume ('market freeze') in times of systemic distress.

7.2 Counterfactuals

7.2.1 No Change in Risk, v_l, q_h

To have a better understanding of the critical importance of risk to our mechanism, I run another simulation of the model in which systemic distress is not characterized by a change in the riskiness of assets or in the cost of bearing risk. I do so by setting v_l^c and q_h^c to equal v_l^g, q_h^g correspondingly. Besides that, I am using the calibrated values appearing in Table 8. In this setting, systemic distress means two things: (i) a decline in dealers' capacity to absorb inventories, embedded in the rise in π between the pre-crisis and the crisis period, and (ii) stronger demand for liquidity by customers, reflected in an increase in the share of distressed sellers, ξ. As we shall see, absent a rise in risk these forces do not imply any substantial correlation between concentration and liquidity during distress.

In figure 8 I plot the predicted behavior of spreads during a crisis when assuming no changes in v_l, q_h in response to a crisis. As a benchmark, I plot next to it the prediction from the original model used above, which is the one that incorporates all the calibrated values. In figure 9, I do the same with volume change.

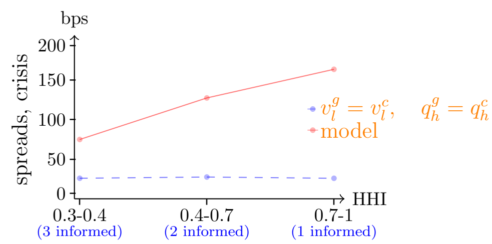

Figure 8: Spreads in the crisis period: model with and without changes in assets composition

Note: The data relied upon to generate this figure was TRACE Data provided by FINRA's TRACE System.

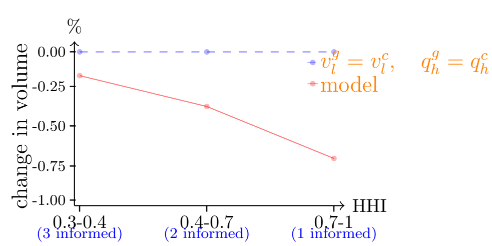

Figure 9: Volume response to the crisis: model with and without changes in asset composition

Note: The data relied upon to generate this figure was TRACE Data provided by FINRA's TRACE System.

In the figure, we can see that absent an increase in uncertainty, the simulation implies results that are both quantitatively and qualitatively different. Volume is not affected at all since any customer that is not serviced by the informed can (and does) end up trading with someone that is uninformed. Spreads in crisis times are actually somewhat lower compared to the pre-crisis period. The reason is that the capital shortage among informed dealers increases the likelihood that a customer who trades with the uninformed is holding a high-quality bond. As a result, the uninformed bid more aggressively. That results in shifting the lower bound of the bid of the informed to a higher point. This mechanism can also explain the surprising fact that in this setting, spreads are declining in the transition from 2 informed players to 1 (!).

These results highlight the strong connection between an increase in uncertainty and the impact of market power on the performance of OTC markets. In times of heightened uncertainty, market power has a much more substantial impact. This happens because, in such times, informed dealers are not constrained by the threat of business stealing by the uninformed. We find a very substantial rise in the cost of risk during the Covid-19 crisis. When we examine this rise through the lens of our model, we find that it was an essential condition for the co-movements of market power with spreads and volume that we find in the data.

7.2.2 No Change in Dealers' Capacity, π

Now, let us study what would have happened if there was no change in the likelihood that a dealer successfully submits a bid. That is, consider a case in which $\pi^c = \pi^c$. Hence, a crisis is merely a change in the demand for liquidity, embedded in ξ, and in the level of adverse selection, implied by $v_l^g, v_l^c, q_h^g, q_h^c$.

Note that in our model, π captures the impact of dealers' capital constraints on spreads and volume. As we explained above, dealers' holding costs do not impact the gap between the inter-dealer price and the customer-to-dealer price directly. However, it may affect it indirectly by making it harder for the customer to find a dealer who will have the needed liquidity to buy the security. In our model, this is captured by π. Note that the assumption that capital constraints are a property that our model shares with canonical search-theory models in the spirit of Duffie et al. (2005). In the few models that embed holding cost into a search framework (for instance, Cohen et al. (2022)), an increase in holding costs increases spreads by making it harder to find a dealer that can answer the customer's demand.

In Figures 10 and 11 I plot the behavior of spreads in a crisis and of volume change for a simulation in which I fix π alongside the same variables in the benchmark model. We see that the interaction of capital constraints and market power has a substantial impact on the behavior of spreads during a crisis. Absent a change in dealers' capital constraint, the increase in spreads due to market power is lower but still sizeable at about 50% of what it would have been if the capital constraints were in place. Similarly, the decline in volume across bonds with varying levels of concentration is milder but yet substantial. For bonds with an HHI between 0.3-0.4, the decline without tightening capital constraints is 11%, rather than 15% in their presence, for bonds with an HHI between 0.4-0.6 it is 23% rather than 35%, and for bonds with an HHI greater than 0.6 it is 48% rather than 71%.

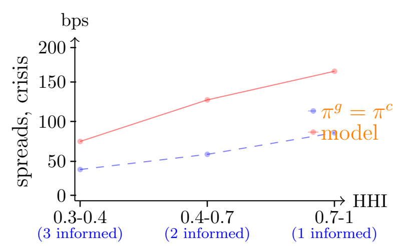

Figure 10: Spreads in the crisis period: model with and without tightening capital constraints
Note: The data relied upon to generate this figure was TRACE Data provided by FINRA's TRACE System.

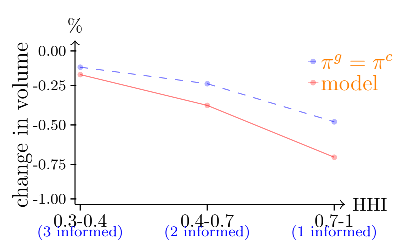

Figure 11: Volume response to the crisis: model with and without tightening capital constraints.
Note: The data relied upon to generate this figure was TRACE Data provided by FINRA's TRACE System.

In other words, without tightening dealers' capital limitations, the impact of concentration on liquidity in dealer markets is lessened. This occurs because such constraints can incapacitate some dealers, reducing competition for the remaining ones. The more moderate shift in volume and spreads during distress in a simulation that sets $\pi^c = \pi^g$ highlights the significance of capital constraints in creating monopolistic inefficiencies in OTC markets during crises. Simultaneously, we see that even without increased capital restrictions, concentration significantly exacerbates the decline in liquidity during systemic distress. This is due to other factors that enhance dealers' competitive edge during a crisis, particularly the heightened uncertainty and the urgent demand for liquidity among their clients. The takeaway is that alleviating dealers' capital constraints is insufficient to restore liquidity.

8 Conclusion

The main takeaway from the paper is that concentration in OTC markets may very well be a concern for financial stability. The dramatic decline in the performance of these markets in a crisis, embedded in higher spreads and lower volumes, seems to be driven, to some extent, by dealers preying on the distress of their customers to collect higher rents. In that sense, the competitive structure of OTC markets ought to be considered as a

Another significant insight is the highly segmented nature of intermediation in the bond market. It underscores that dealers' capital does not fluidly circulate from one bond to another. The restricted flow of liquid funds among dealers could significantly disrupt the market, while increased trading activities by some dealers might not adequately counterbalance the reduced activities of others. This emphasizes the importance of heterogeneity in dealers' performance, which might be more impactful to the market than previously assumed.

Lastly, this paper brings to light an unanticipated process by which adverse selection amplifies market power and heightens losses from monopolistic inefficiency. The vital role of adverse selection contrasts starkly with the dealers' capacity constraints, which are deemed non-essential for trade to become "clogged" within the dealer sector. Consequently, an unexpected implication arises that merely alleviating the tightening of dealers' capacity constraints might prove insufficient to restore market liquidity.

9 Empirical Results Appendix:

Dependent Variable:			spread			
		COVID-19 Crisis			GRC	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
HHI	5.7*** (1.4)	13.7*** (1.1)	0.64 (0.92)	-0.01 (5.9)	9.3** (4.1)	-0.21 (3.2)
HHI × crisis indicator	27.6*** (8.4)	92.0*** (9.8)	-43.2*** (9.6)	2.0 (8.4)	16.0*** (5.7)	-8.4* (4.3)
rule 144a	-2.2*** (0.78)	-7.1*** (0.60)	3.1*** (0.53)	-2.0 (2.1)	-30.0*** (3.1)	18.0*** (2.9)
sqrt(age)	0.08*** (0.02)	-0.11*** (0.01)	0.25*** (0.01)	0.19*** (0.04)	-0.36*** (0.04)	0.55*** (0.03)
sqrt(time to maturity)	0.28*** (0.01)	0.20*** (0.01)	0.35*** (0.01)	0.47*** (0.06)	0.48*** (0.03)	0.49*** (0.02)
sqrt_amtout_issr	-1.9×10^{-5}*** (3.3×10^{-6})	-5.1×10^{-5}*** (2×10^{-6})	1×10^{-5}*** (1.6×10^{-6})	-4.8×10^{-6} (5×10^{-6})	-1.9×10^{-5}*** (4.7×10^{-6})	6.1×10^{-7} (3.1×10^{-6})
sqrt(amount outstanding)	-0.0001*** (1.1×10^{-5})	-0.0002*** (1×10^{-5})	-6.8×10^{-7} (8×10^{-6})	-0.0002** (7.3×10^{-5})	-0.0004*** (5.9×10^{-5})	1.6×10^{-5} (4.6×10^{-5})
coupon rate	0.33 (0.26)	2.3*** (0.15)	-1.6*** (0.13)	-0.14* (0.07)	-0.04 (0.06)	-0.23*** (0.05)
foreign	-0.07 (0.64)	-1.3** (0.68)	1.2** (0.58)	-6.3** (2.5)	-7.8*** (2.1)	-1.7 (1.7)
global	0.41 (0.38)	-0.52** (0.26)	1.2*** (0.21)	-2.2*** (0.74)	-10.2*** (0.87)	5.0*** (0.63)
finance	0.28 (0.37)	-1.9*** (0.29)	2.0*** (0.27)	14.1*** (2.2)	9.0*** (1.0)	12.4*** (0.77)
utility	-0.71 (1.2)	-3.0*** (0.57)	1.6*** (0.49)	-5.9*** (2.0)	-13.1*** (1.7)	1.3 (1.5)
Fixed-effects						
rating	Yes	Yes	Yes	Yes	Yes	Yes
trade size	Yes	Yes	Yes	Yes	Yes	Yes
dealer	Yes	Yes	Yes	Yes	Yes	Yes
dealer-date	Yes	Yes	Yes	Yes	Yes	Yes
date	Yes	Yes	Yes	Yes	Yes	Yes
# days traded (prv. year)	Yes	Yes	Yes	Yes	Yes	Yes
# days traded (prv. year)-date	Yes	Yes	Yes	Yes	Yes	Yes
rating-date	Yes	Yes	Yes	Yes	Yes	Yes
trade size-date	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	1,375,793	656,133	719,660	621,479	271,191	350,288
R^2	0.11938	0.25548	0.21531	0.19310	0.36171	0.36307
Within R^2	0.00693	0.00936	0.01212	0.00485	0.00735	0.00997

Clustered (rating) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 9: Results from applying the standard model (eq 3) to the Covid-19 crisis and the period proceeding it and to the GRC and the period proceeding it; Full. Note: The data relied upon to generate this table was TRACE Data provided by FINRA's TRACE System

Define $CRi_{b,t}, i \in \{1, 2, 3, 4\}$ as the share of trade in a bond b in year t that is facilitated by the i dealers who trade most extensively at the bond. Again, analogous measures for issuers are created and applied to different sub-segments of the market.

9.0.1 Concentration at the Bond Level

Figure 12 represents the distribution of CR3 - the share of trade in a market for a bond that is accounted for by the three dealers who trade it most intensively (i.e: have the largest market share in terms of volume).

The solid line boxplot represents the bond-level CR3 that is computed based on all trades in the market. For more than 50% of the bond, more than 55% of the volume is traded solely by three dealers. For the sake of comparison, CR3 of the market as a whole appears on the plot as an X mark. The market-wide HHI is 27% - less than half of the bond-level median

Dependent Variable:	spread									
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables										
HHI	10.1*** (1.1)	16.4*** (1.7)	18.1*** (1.7)	18.4*** (1.5)	17.6*** (1.6)	18.4*** (1.5)	18.5*** (1.5)	18.3*** (1.5)	16.8*** (1.5)	16.3*** (1.5)
HHI × crisis indicator	159.5*** (0.83)	108.6*** (11.6)	108.0*** (11.6)	87.9*** (11.1)	85.9*** (11.5)	89.0*** (10.9)	89.0*** (10.9)	90.9*** (10.6)	91.7*** (10.5)	88.4*** (10.1)
(Intercept)	13.8*** (0.64)									
rule 144a	-9.1*** (0.34)	-9.8*** (1.1)	-9.2*** (1.2)	-9.5*** (1.2)	-7.9*** (1.1)	-7.9*** (1.0)	-7.8*** (1.0)	-7.7*** (1.0)	-7.0*** (0.98)	-7.0*** (0.92)
sqrt(age)	-0.14*** (0.007)	-0.15*** (0.02)	-0.14*** (0.02)	-0.15*** (0.02)	-0.08*** (0.02)	-0.06*** (0.02)	-0.07*** (0.02)	-0.07*** (0.02)	-0.11*** (0.02)	-0.12*** (0.02)
sqrt_amtout_issr	$-5.7\times10^{-5***}$ (1.4×10^{-6})	$-5.2\times10^{-5***}$ (2.8×10^{-6})	$-5.1\times10^{-5***}$ (3×10^{-6})	$-5.2\times10^{-5***}$ (3×10^{-6})	$-5.3\times10^{-5***}$ (3×10^{-6})	$-5.3\times10^{-5***}$ (3.1×10^{-6})	$-5.3\times10^{-5***}$ (3.1×10^{-6})	$-5.2\times10^{-5***}$ (3×10^{-6})	$-4.9\times10^{-5***}$ (2.9×10^{-6})	$-4.9\times10^{-5***}$ (2.9×10^{-6})
sqrt(time to maturity)	0.07*** (0.002)	0.07*** (0.01)	0.07*** (0.010)	0.07*** (0.010)	0.24*** (0.03)	0.24*** (0.03)	0.24*** (0.03)	0.24*** (0.03)	0.24*** (0.03)	0.23*** (0.03)
sqrt(amount outstanding)	-0.0001*** (6.1×10^{-6})	-0.0002*** (1.3×10^{-5})	-0.0002*** (1.9×10^{-5})	-0.0002*** (1.9×10^{-5})	-0.0003*** (2×10^{-5})	-0.0003*** (1.8×10^{-5})	-0.0003*** (1.8×10^{-5})	-0.0003*** (1.8×10^{-5})	-0.0003*** (1.7×10^{-5})	-0.0003*** (1.7×10^{-5})
coupon rate	3.4*** (0.07)	3.3*** (0.19)	3.3*** (0.19)	3.3*** (0.19)	1.4*** (0.22)	1.5*** (0.19)	1.5*** (0.19)	1.5*** (0.19)	1.7*** (0.19)	1.7*** (0.19)
foreign	-5.9*** (0.47)	-5.5*** (0.79)	-5.7*** (0.82)	-5.3*** (0.81)	-1.5* (0.86)	-1.8** (0.81)	-1.8** (0.81)	-1.8** (0.81)	-1.6** (0.81)	-1.8** (0.83)
global	0.18 (0.20)	0.04 (0.40)	-0.03 (0.40)	-0.007 (0.40)	0.04 (0.29)	-0.14 (0.27)	-0.18 (0.27)	-0.21 (0.27)	-0.22 (0.27)	-0.34 (0.28)
finance	-4.8*** (0.22)	-4.5*** (0.43)	-4.5*** (0.42)	-4.5*** (0.42)	-1.2*** (0.42)	-1.1*** (0.42)	-1.1*** (0.42)	-1.2*** (0.41)	-1.2*** (0.41)	-1.3*** (0.40)
utility	-5.7*** (0.39)	-5.6*** (0.93)	-5.3*** (0.89)	-5.4*** (0.83)	-4.6*** (0.73)	-3.8*** (0.63)	-3.7*** (0.63)	-3.7*** (0.63)	-3.3*** (0.62)	-2.9*** (0.62)
Fixed-effects										
date		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# days traded (prv. year)			Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# days traded (prv. year)-date				Yes	Yes	Yes	Yes	Yes	Yes	Yes
rating					Yes	Yes	Yes	Yes	Yes	Yes
rating-date						Yes	Yes	Yes	Yes	Yes
trade size							Yes	Yes	Yes	Yes
trade size-date								Yes	Yes	Yes
dealer									Yes	Yes
dealer-date										Yes
Fit statistics										
Observations	883,600	883,600	883,600	883,600	874,895	874,895	874,895	874,895	874,895	874,895
R^2	0.04993	0.10811	0.10832	0.12570	0.12957	0.17713	0.17758	0.18346	0.19354	0.23565
Within R^2		0.01238	0.01053	0.01030	0.00983	0.01007	0.01008	0.01007	0.00967	0.00941

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 10: Cumulative FE in the standard model (eq 3) for the COVID-19 crisis. Note: The data relied upon to generate this table was TRACE Data provided by FINRA's TRACE System

Concentration in the US Corporate Bonds Market

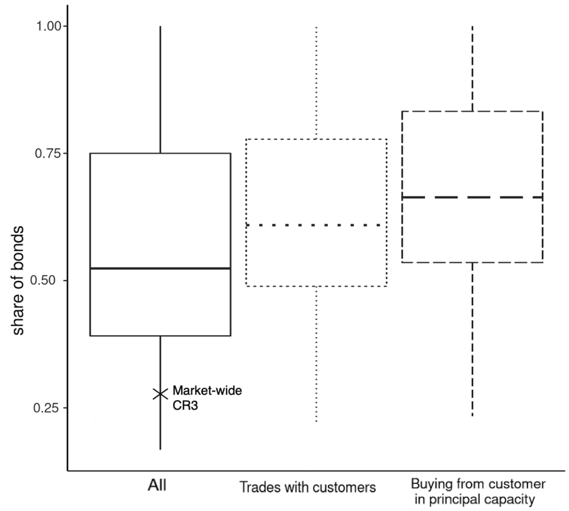

Figure 12: Distribution in the share of trade of the three leading dealers for each bond, 2006-2020.
Note: The data relied upon to generate this figure was TRACE Data provided by FINRA's TRACE System.

CR3. Also, on average, each of the three largest dealers in the market accounts for 9% of the entire volume. That does not seem, at least on the surface, to be a concentrated market.

Lastly, given that dealers specialize by issuer, one might think it is proper to consider the market segmented across issuers rather than bonds. To see if this is the case, Figure 13 focuses on dealers accounting for more than 10% of the trade in an issuer's bonds. It plots the deviation of their share of trade in each bond from their share of trade in all the issuers' securities.

When a dealer trades an issuer's securities, it trades many of them quite heavily. However, it also refrains from trading others altogether. That is, while they focus on securities of a subset of issuers, within each issuer, they focus on a subset of bonds. For instance, that could result from the type of clients the dealer is working with. For example, bonds with one year left to maturity are traded by money-market funds. It makes sense that only dealers connected to such players will intermediate such bonds, even if the dealer is familiar with the issuer and can assess the likelihood of default. Also, bonds can be highly heterogeneous and complex assets. Thus, familiarity with the issuer is insufficient to determine its security value. Given this context, Table 4 shows that bonds with a low amount outstanding will typically be traded by fewer dealers vis-a-vis other bonds issued by the same issuer. Again,

Histogram of dealers share of a bond vs. share of all issuers bonds, 2019

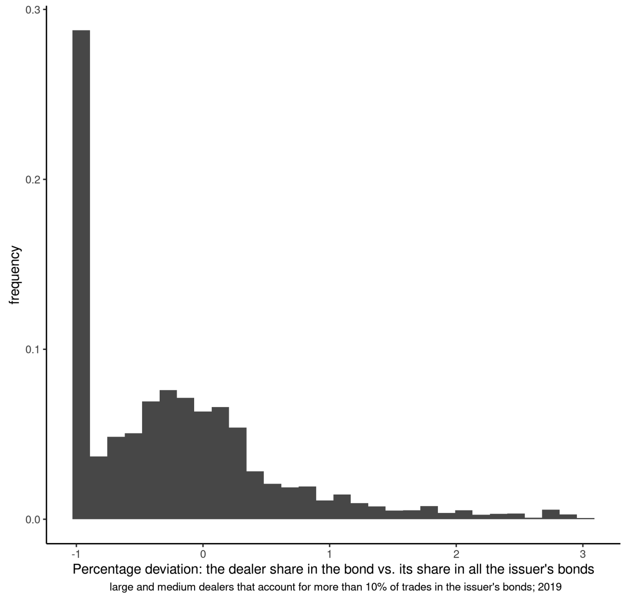

Figure 13: Trading an issuer does not mean trading all its bonds.
Note: The data relied upon to generate this figure was provided by FINRA's TRACE System.

the amount outstanding can be considered a proxy for market size, and the larger the market for a bond, the greater the number of dealers that will pay the cost of assessing its actual value. Because of this pattern, markets will be regarded as segmented at the bond level throughout this paper.

9.1 The Correlation of Concentration and Rising Spreads in Crisis

For the following analysis, I begin by running the regression model in equation 3 with one minor change - rather than treating the HHI as a continuous variable, I divide it into bins and regard it as a categorical variable. I choose bins at the length of 10 bps, besides the bins at the edges, 0-0.3 and 0.6-1, that span over a wider range to compensate for these levels being much more sparsely populated. The coefficients and 95% confidence intervals from applying these regressions to the COVID-19 crisis appear in plot 14. Again, they present these coefficients for the entire sample (black), for trades in which a customer sells to a dealer (red), and for trades in which a dealer sells to a customer (blue). Let us begin with trades in which a customer sells to a dealer. We see a pattern that looks almost like a linear upward slope, indicating that higher HHI levels presage a greater increase in spreads. The results are statistically significant, with the 95% confidence interval being far above zero. An important feature to note is the positive and sizeable coefficients at HHI levels of 0.3-0.4 and 0.4-0.5. This indicates that even when comparing a competitive market, that is HHI of 0-0.3, to somewhat less competitive markets, like the one with an HHI of 0.3-0.4, we see a change in the response of spreads to a crisis. This is critical as about 80% of trade volume during a crisis is trade in bonds with an HHI of 0.3-0.5 (see 11). Hence, changes in the behavior of these bonds in a crisis can have a sizable impact on the aggregate behavior of the market.

For the coming analysis, I apply a few additional filters to the data. I limit my attention to principal trades. Also, I ignore retail trades and incorporate only transactions with a volume of $100,000 or more. I do so since retail trades constitute the majority of observations but only 10% of total trade volume. Hence, incorporating these observations may generate results that apply to them and actually have very little impact on most of the volume traded. To preserve consistency with previous parts of the work, I focus only on trades conducted by the top 50 dealers, who account for about 99.7% of trade volume. I measure concentration using bond-level HHI generated from trades in which dealers buy from customers in a risky principal capacity. To the best of my understanding, this measures the concentration that has an impact according to the theory that underlies this paper, that is, the concentration that dictates the alternatives that a customer who wishes to sell a bond in principal capacity is facing. To avoid bias due to reverse causality, I calculate the HH index for each transaction based on trades in the bond traded in the previous year, $t-1$.

Alongside this, I apply a few filters to address potential weaknesses of the spread measure. That is more true for less liquid bonds, as the infrequent trade makes such a rapid sequence of trades in the bonds highly unlikely. I ignore trades in which the time that has elapsed since the benchmark trade took place is greater than seven days. I do so to minimize the effect of fundamental changes in the price of the bond over time on the differences that the data exhibits between customer-to-dealer versus dealer-to-dealer bonds. Further, as a robustness test, I run the tests of my hypothesis also on a more limited sample of transactions for which the benchmark trade occurred at the same day as the trade itself. I winsowrize the spreads to diminish the risk of bias due to outliers. I set the higher bound of the spreads to be the

95% quantile plus 1.5 times the interquartile range, and the lower bound to the 5th quantile minus 1.5 the interquartile range.

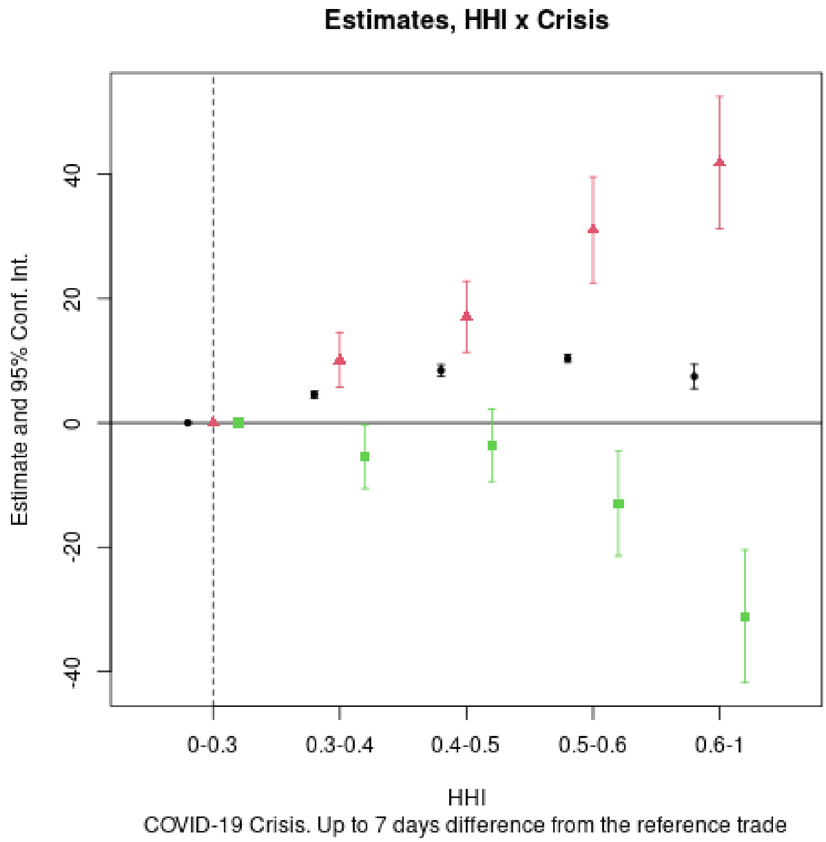

Figure 14: Results from applying the standard model (eq 3) to the Covid-19 crisis and the period proceeding it while treating the bond HHI as a categorical variable. Note: The data relied upon to generate this table was TRACE Data provided by FINRA's TRACE System

HHI	share of volume
0-0.3	0.11
0.3-0.4	0.59
0.4-0.5	0.19
0.5-0.6	0.06
0.6-0.7	0.02
0.7 - 1	0.02

Table 11: The share of volume bought by dealers in principal capacity by the bond HHI during the Covid-19 crisis.
Note: The data relied upon to generate this figure was TRACE Data provided by FINRA's TRACE System.

With trades in which dealers sell to customers the pattern is a bit more complex. There, we see a sizable and statistically significant difference only at HHI levels that are greater than 0.5. There are two things to keep in mind about results that persist in this range. First, since there are fewer trades in bonds with this HHI in the sample, the result is more susceptible to error. Second, note that in a market for a bond that with a single market maker dealer may not have a substantial advantage over customers. In such a market, dealers' ability to easily find and trade with any other dealer is less likely to grant them access to multiple potential counter-parties. Thus, the market maker may exploit other dealers' distress to buy cheap from them and sell at a higher price to a customer. That will appear as a negative spread.

A concern that may arise is that the pattern we find in the dealer-to-customer trades reflects changes in the fundamental prices of bonds over time. More specifically, a decline in fundamental prices of bonds will mechanically turn the benchmark price, determined by an earlier trade between two dealers, to a higher price than the current trade price. The change will be more pronounced for less liquid bonds, for which the trades are typically more far apart. As higher concentration is typically correlated with lower liquidity, we will get a bias that operates in the same direction as our coefficients - it will imply that in more concentrated markets, customers sell and buy at a higher discount. That will be manifested in a positive coefficient on the interaction term of HHI and a crisis in customer-to-dealer trades, and a negative coefficient in dealer-to-customer trades.

To address this concern, I run the same regression with HHI bins again, but this time I limit my sample to trades for which the dealer-to-dealer trade that determines the benchmark price to calculate the spreads occured in the same day as the trade itself. The results appear in plot 15. What we can see is that the pattern of higher increase in coefficients for more concentrated markets in trades in which customers sell to dealers persists. The coefficients are about the same sizes as before and are all statistically significant at 1% confidence level. In contrast, the results for trades in which dealers sell to customer are less salient. Besides 0.6-1, neither of the other bins implies a statistically significant decline in spreads across markets with varying levels of competition. In other others, much of the correlation between higher HHI and lower spreads in dealer-to-customer spreads is indeed spurious and driven by changes in fundamental prices. In contrast, such changes do not seem to drive the correlation in trades in which customers sell to dealers.

In plots 16 and 17 we see a similar pattern in the 2007-2009 crisis. Again, we see that the coefficients on the interaction term between HHI and the crisis indicator are all positive, sizeable, and statistically significant. They exhibit an upward trend. There is a break in that pattern as the coefficient on the interaction term on the range between 0.6-1 is smaller than the one in the range of 0.5-0.6. However, even a glance with the naked eye at the confidence intervals of the two we can see that this difference is not statistically significant. These results persist when we limit out attention to cases when the benchmark trade occurred on the same day as the trade itself. In contrast, with trades in which dealers sell to customer the pattern is more complex. The coefficients on the interaction term with the crisis indicator for HHI of 0.3-0.4 and 0.6-1 are close to zero and not statistically significant. Limiting our attention to cases when the benchmark trade occurred on the same day, the interaction term for HHI of 0.5-0.6 losses statistical significant as well and the overall pattern of coefficients does not exhibit a clear monotonic pattern dominating the relationship between HHI and the rise in spreads in a crisis.

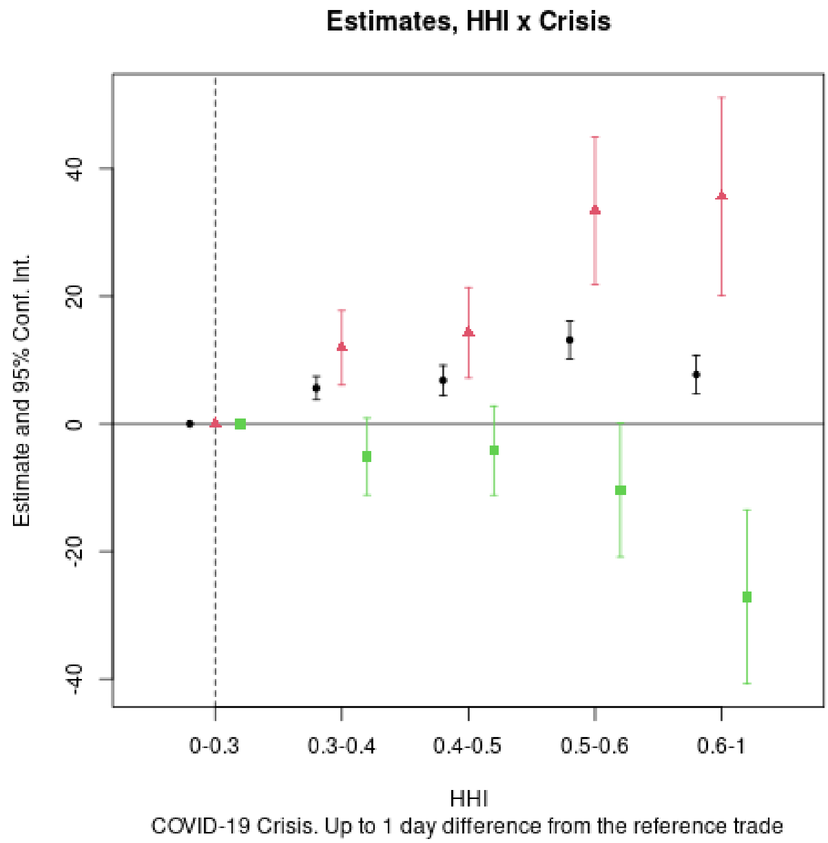

Figure 15: Results from applying the standard model (eq 3) to the Covid-19 crisis and the period proceeding it while treating the bond HHI as a categorical variable. Limiting to cases in which the transaction that generated the reference price occurred at the same day as the trade itself.
Note: The data relied upon to generate this table was TRACE Data provided by FINRA's TRACE System

As a further robustness test, I run an alternative regression model:

$$\begin{aligned} Spread_{i,d,b,t} = \alpha_0 + \rho_b * \eta_d * \nu_i + \beta_2 * HHI_{b,t-1} * \mathbb{I}\{Crisis\} + \\ \eta_d + \text{trade\_date} + \\ \eta_d * \text{trade\_date} + \xi_b * \text{trade\_date} + \nu_i * \text{trade\_date} + \lambda_b * \text{trade\_date} \end{aligned} \quad (8)$$

In this model, I control for an interaction term of a bond-dealer-volume fixed effect ($\rho_b * \eta_d * \nu_i$). Thus, the model compares trades made by the same dealer, trading the same bond, in the same volume (bin) before and during a crisis. The control for a bond fixed effect makes the use of bond attribute controls redundant (but not the use of interaction terms between those

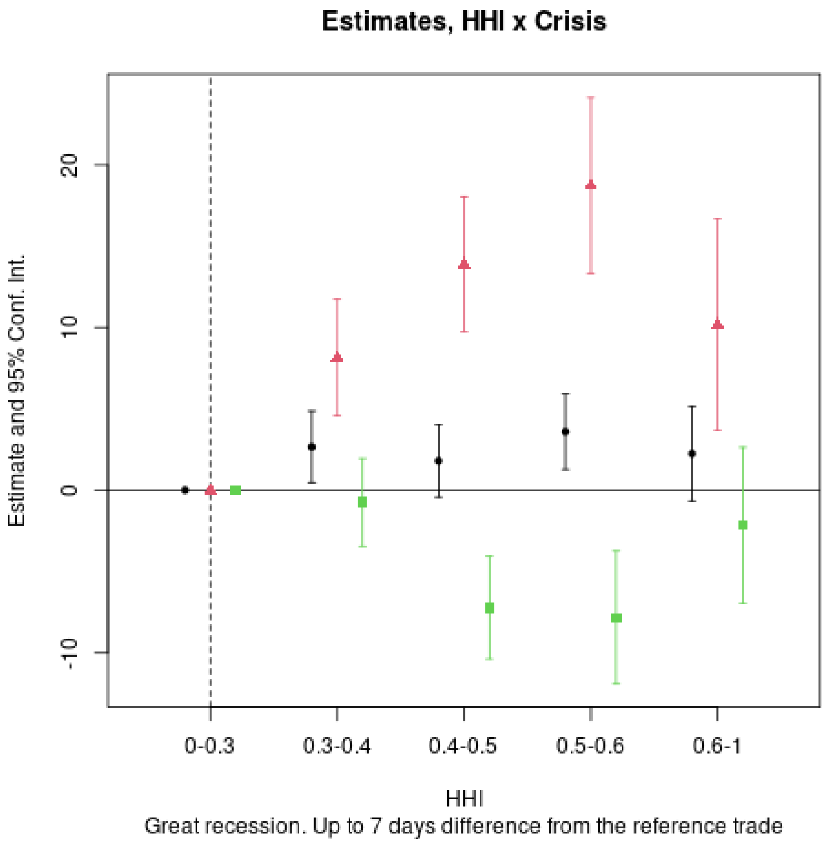

Figure 16: Results from applying the standard model (eq 3) to the 2007-2009 crisis and the period proceeding it while treating the bond HHI as a categorical variable. Note: The data relied upon to generate this table was TRACE Data provided by FINRA's TRACE System

terms and the date). On a deeper level, it prevents potential bias due to the omission of bond attributes. In this regression, the "jump" in the spreads that a dealer will charge consists of an average increase in the spreads due to the crisis time, embedded into the trade date fixed effect, in addition to the term $\beta_2 * HHI_{b,t-1} * \mathbb{I}\{Crisis\}$. The latter captures the same correlation that it embedded in the original model appearing in equation 3: the expected differences in the "jump" for bonds with varying levels of concentration. For the same reasons explained before, I control for the interaction term between dealer, rating, and liquidity fixed effects and the date. The results appear in plot 18.

The result for customer-to-dealer trade remains almost exactly the same as in the original regression model. In contrast, the coefficients on the interaction term between HHI and a crisis for trades in which dealers sell to customers hover around zero for any HHI besides

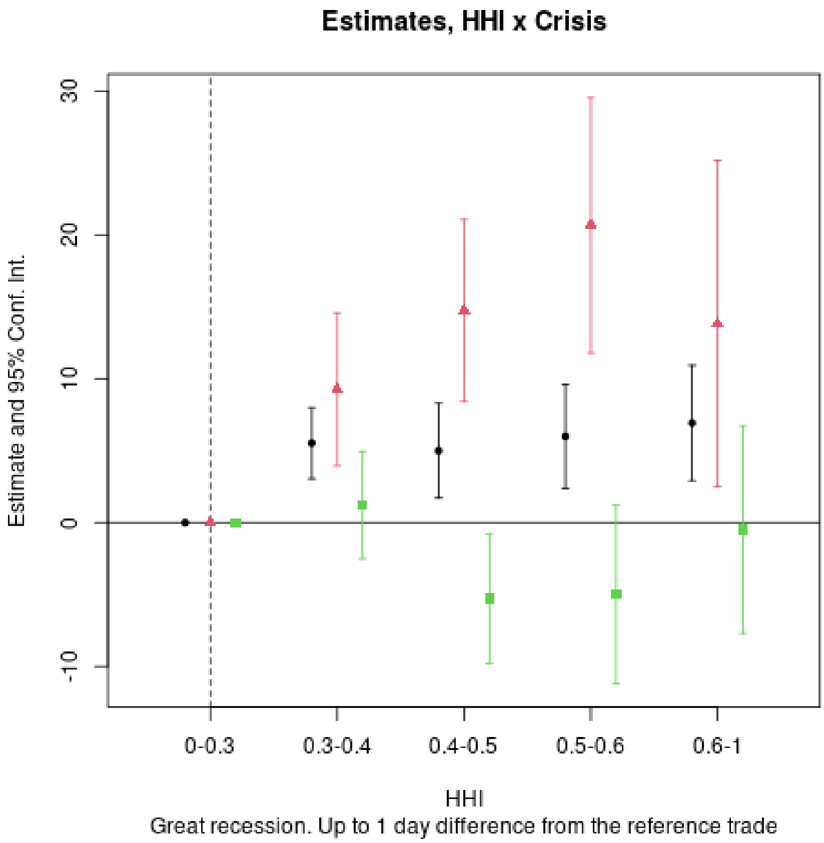

Figure 17: Results from applying the standard model (eq 3) to the 2007-2009 crisis and the period proceeding it while treating the bond HHI as a categorical variable. Limiting to cases in which the transaction that generated the reference price occurred on the same day as the trade itself.
Note: The data relied upon to generate this table was TRACE Data provided by FINRA's TRACE System

0.6-1, where they appear negative. That, again, may reflect dealers praying on the distress of other dealers to buy at substantial discounts. Either way, this is evidence of the robustness of the correlation between concentration and the rise in spreads paid by customers that seek to attain liquidity during a crisis. In contrast, the support that the data lends to correlations between the change in spreads in a crisis and the bond HHI for trades in which dealers sell to customers, which are not implied by the logic that guides this paper, seems much more ambiguous. Thus, from this point on, I focus merely on customer-to-dealer trades.

Now, I run a few more robustness tests. First, I run another regression model with an alternative liquidity measure. Rather than using the number of days in which the bond was

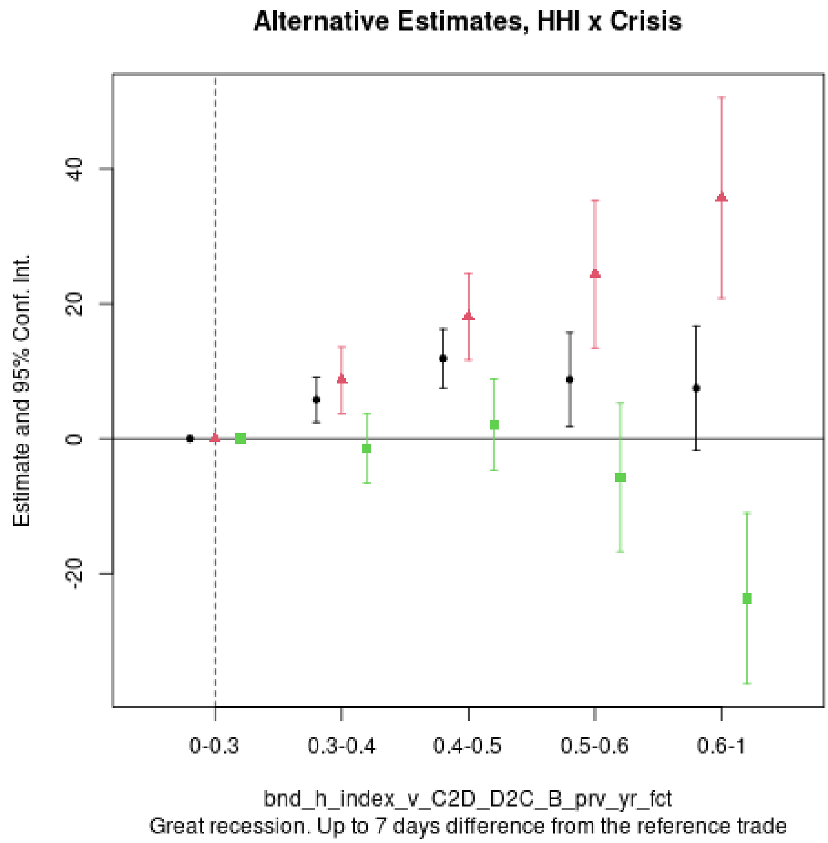

Figure 18: Results from applying the regression model in equation 8 to the COVID-19 crisis and the period proceeding it. HHI is treated as a categorical variable.
Note: The data relied upon to generate this table was TRACE Data provided by FINRA's TRACE System

not traded, I use the median of the difference between the time that a dealer purchases a bond and the next time he gets to sell it. That serves as a proxy of the expected holding period. To avoid bias due to the presence of agency trades, I ignore cases in which the dealer holds the bonds for less than one day. For each trade, I calculate this statistic based on trades of the bond in the previous year to avoid bias due to reverse causality. Further, I change this proxy into a categorical variable by dividing it into bins by percentiles, with each bin covering a range of 5 percentiles.

The main reason to run the regression with this liquidity measure is to address a concern for bias due to the thinness of the inter-dealer market for bonds with high levels of HHI. Concentration implies that a dealer will have greater difficulty selling the bond to another dealer to attain liquidity. That may lead a dealer to require a higher compensation, manifested in greater spread. That is especially true during a crisis when the cost of committing capital to hold a bond for a prolonged period of time in the dealers' portfolio greatly increases. The control for the dealer's expected holding period mitigates this concern. Bonds that do not easily trade in the inter-dealer market will have a longer holding period, as a dealer will be less likely to address transient liquidity needs by trading them. Hence, this liquidity measure will capture costs imposed on the dealer that originate from the breadth of the inter-dealer market.

The results of this regression appear in column (2) of table 12. We see that the inclusion of this liquidity measure diminishes the interaction term of HHI and the crisis indicator from 90 bps to 75 bps. Thus, while this dimension of liquidity may have a role in shaping spreads, it cannot account for the correlation between concentration and the rise in spreads in crisis we find in the data.

Dependent Variable:	spread		
Model:	(1)	(2)	(3)
Variables			
HHI	13.7*** (1.1)	15.3*** (1.5)	
HHI × crisis indicator	92.0*** (9.8)	89.8*** (10.0)	71.0*** (26.0)
rule 144a	-7.1*** (0.60)	-7.7*** (0.90)	-339.5 (1,038.1)
sqrt(age)	-0.11*** (0.01)	-0.11*** (0.02)	0.99** (0.45)
sqrt(time to maturity)	0.20*** (0.01)	0.24*** (0.03)	0.65** (0.26)
sqrt_amtout_issr	$-5.1 \times 10^{-5***}$ (2×10^{-6})	$-4.8 \times 10^{-5***}$ (2.6×10^{-6})	0.001 (0.003)
sqrt(amount outstanding)	-0.0002*** (1×10^{-5})	-0.0002*** (1.5×10^{-5})	-0.0003 (0.01)
coupon rate	2.3*** (0.15)	1.6*** (0.19)	1.1 (0.72)
foreign	-1.3** (0.68)	-2.1** (0.81)	756.7 (2,746.5)
global	-0.52** (0.26)	-0.16 (0.28)	192.7 (752.1)
finance	-1.9*** (0.29)	-1.3*** (0.41)	-1,057.7 (822.0)
utility	-3.0*** (0.57)	-3.4*** (0.64)	-1,266.6 (1,691.3)
Fixed-effects			
rating	Yes	Yes	Yes
trade size	Yes	Yes	Yes
dealer	Yes	Yes	Yes
dealer-date	Yes	Yes	Yes
date	Yes	Yes	Yes
# days traded (prv. year)	Yes		Yes
# days traded (prv. year)-date	Yes		Yes
rating-date	Yes	Yes	Yes
trade size-date	Yes	Yes	Yes
exp. holding time		Yes	
exp. holding time-date		Yes	
HHI			Yes
issuer			Yes
issuer-date			Yes
Fit statistics			
Observations	656,133	874,707	1,270,641
R^2	0.25548	0.23435	0.70151
Within R^2	0.00936	0.00904	0.00024

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 12: Comparing the standard model (eq 3) to two other benchmarks for the COVID-19 crisis: one using expected holding time as a liquidity measure and the other including issuer fixed effects.
Note: The data relied upon to generate this table was TRACE Data provided by

Now, we also run our original regression model with an issuer fixed effect. By that, we compare bonds of the same issuer traded in the market with varying concentration levels. That can be caused, for instance, by institutional constraints that prevent certain dealers who are familiar with the issuer from trading some of its bonds. The reason for including the issuer's fixed effects is to control for potential supply shocks. That is, it mitigates the concern that concentration is correlated with features of the bond that make it more appealing to specific types of customers. Thus, the correlation of concentration and spreads may simply represent the fact that those customers were subject to more dire liquidity shocks during the crisis [7].

The results appear in column (3) of Table 12. Again, while a dealer fixed effect diminishes the coefficient on the interaction term from 90 to 71, yet the coefficient remains statistically significant and sizable.

Lastly, in table 10, I gradually add fixed effects to a regression to arrive at the main model appearing in equation 3. What we can see is that the addition (or omission) of fixed effects has very little impact on the regression. Overall, the coefficients remain very stable at a level of about 90 bps. This is further evidence of the robustness of the main result and its independence from the specifics of the regression model that was chosen.

As mentioned, the analysis is not founded on random assignment of treatment, and hence the coefficients cannot be interpreted as proper estimates of the causal impact of concentration on spreads. However, while they cannot provide a precise measure, they may imply an order of magnitude that allows interpreting the relevance of concentration in OTC markets to the rise in the cost of trading (spreads) in a crisis. For that purpose, I calculate the regression prediction for the increase in spreads in times of crisis in a world with an identical composition of bonds but for the fact that all bonds are traded in highly competitive markets with HHI being lower than 0.3. I weigh the importance of the change in spreads for each HHI bin according to the share of volume traded in the crisis accounted for by bonds in that bin. That is, I compute the weighted sum:

[7] I am grateful to Dasol Kim from the Office of Financial Research for raising this concern and offering to add an issuer fixed effect.

$$\sum_{HHI} \beta_{2,HHI} * \text{volume share}_{\text{HHI}} = 0.59 * 10 + 0.19 * 17 + 0.06 * 31 + 0.04 * 42... \approx 12.6$$

As a benchmark, table 13 presents the volume-weighted spread during the COVID-19 crisis and the period preceding it in customer-to-dealers trades. As we can see, the weighted spread increased by about 64 bps. Hence, the regression predicts that in a fully competitive market, the increase in the spread increaseVID-19 crisis would have been 20%

Period	Mean spread
Pre Covid-19 Crisis	18.57
Covid-19 Crisis	82.57

Table 13: Mean spread charged by dealers when buying from customers on principal capacity (trades over $100,000). Weighted by quantity traded.
Note: The data relied upon to generate this figure was TRACE Data provided by FINRA's TRACE System.

Now, I document the behavior of the volume of trades across different concentration levels. The HHI is divided into categories, and all the volume traded in the bonds included in each bin is summed up. Then, I calculate the percentage change between the total volume of all bonds included in each bin between a time of crisis and a period of similar length that precedes it.

Figure 19 shows the percentage change in volume traded between the Covid-19 crisis and the months that preceded it. One can see that bonds traded by fewer dealers exhibit a more significant relative decline in volume during the Covid-19 crisis. The trend gradually increases with HHI, meaning a more substantial reduction in volume for more concentrated markets. This is important for two reasons. First, this paper's hypothesis implies that dealers will exercise market power more aggressively. They will be more inclined to sacrifice volume to raise the return per transaction. Second, volume is the primary concern of regulators. The

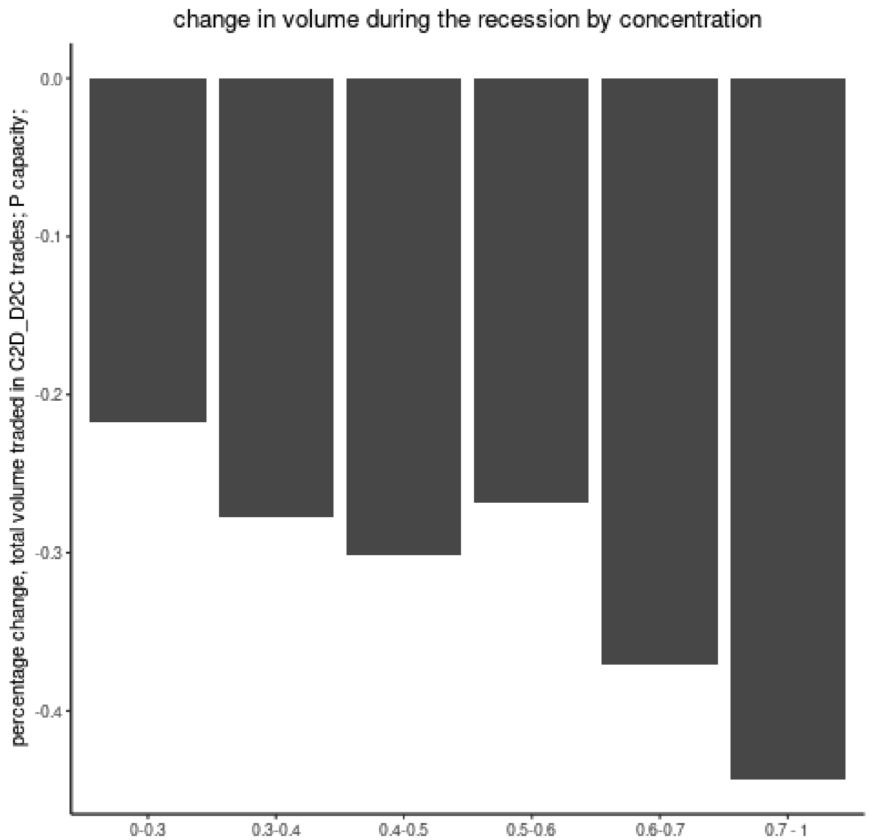

Figure 19: Change in volume bought by dealers in principal capacity by HHI: The Covid-19 crisis and the preceding period.
Note: The data relied upon to generate this figure was TRACE Data provided by FINRA's TRACE System.

problem with dealers' use of market power is not that it generates profits for dealers at the expense of their customers (in fact, some may even see that as a silver lining - improving dealers' access to capital and their ability to keep operating throughout the crisis). Instead, the problem is that when dealers do so, they limit trade and prevent the reallocation of liquidity from customers that are better off to those that are distressed. This can be considered an analogy to the classical monopoly problem, where the concern is the "underproduction" of intermediation services.

The plot implies sizeable differences in the response in volume to distress during a crisis. It is possible to use it, alongside the share of volume traded by HHI level (appearing in Figure 2), to approximate the difference between the decline in volume in a highly competitive market (HHI of 0.3 or less) to what we find in the data. Let Q_{hs} denote the share of trade in bonds with an HHI in the set hs, and let Δ_{hs} denote the decline in volume for bonds in that set.

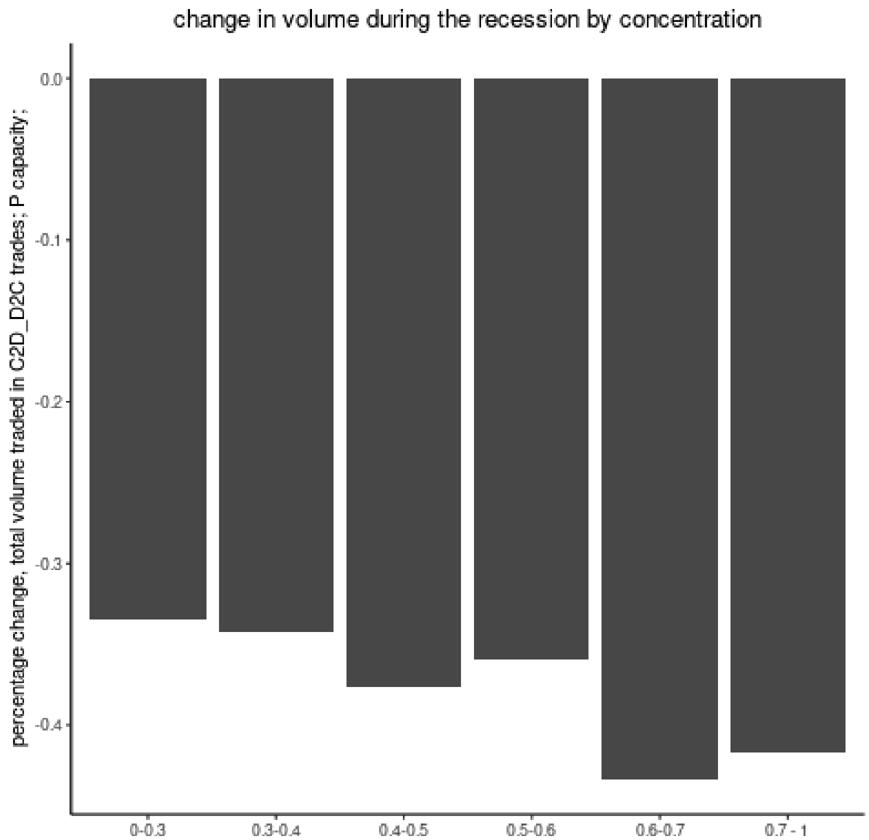

Figure 20: Change in volume bought by dealers in principal capacity by HHI: The 2007-2009 crisis and the preceding period.
Note: The data relied upon to generate this figure was TRACE Data provided by FINRA's TRACE System.

The weighted decline in volume, according to the data, is

$$\sum_{hs} Q_h s * \Delta_{hs} = 0.25*-0.22+0.25*-0.28+0.15*-0.32+0.1*-0.28+0.1*-0.37+0.15*-0.47 = -0.3.$$

The change in volume in a highly competitive market is -0.22. That is, the decline in volume in the market is 36% greater than what we expect in an economy where all markets have an HHI of 0.3 or less. The calibration exercise assesses which part of this difference originates from changes in the way that dealers exercise their market power.

Figure 20 represent the same phenomenon for the 2008 crisis. Here too, there is a correlation between HHI and the decline in volume. However, it is somewhat more muted compared to the Covid-19 crisis.

10 Proofs appendix:

10.0.1 Proof of lemma 6.2

Assume that condition **??** does not hold. It is plain to see that, in this case, the informed cannot break even by giving any bid that may appeal to non-distressed players. If **??** holds, we can show that the uninformed will submit a bid that breaks even that appeals only to distressed customers based on the same logic explained above.

If neither condition holds, $B^U(n^*) < v_h - \delta_s$ and the uninformed bid never wins the high-quality bond. Any bid above v_l will mean paying more than the expected value, while any bid below it will generate a strictly positive payoff, implying the existence of a profitable deviation.

10.0.2 Proof for lemma ??

Proof. The claim states that if informed dealers target only the distressed players with some positive probability, they must entirely refrain from submitting bids on the higher interval range $[v_h - \delta_s, v_h - \delta]$. The intuition is simple: bidding even a bit higher and winning access to another market segment, that is, the non-distressed players, is preferable.

Note that it can never be the case that $F()$ is strictly increasing on an interval $(v_h - \delta - \epsilon, v_h - \delta + \epsilon)$. If there was a range ϵ such that the profits from buying at a bid of $v_h - \delta + \epsilon$ from all customers would strictly dominate buying only from distressed players (ξ of the population) for $v_h - \delta - \epsilon$. □

10.0.3 Proof of lemma ??

Proof. Let $\xi > \frac{\delta}{(v_h - \bar{R}^d)\pi^{n-1}}$. Set $\underline{B}^I = \bar{R}^d$. Note that our assumption implies:

$$\xi(v_h - \bar{R}^d)\pi^{n-1} > v_h - (v_h - \delta)$$

The LHS is the expected return from bidding $\bar{R}^d$, while the RHS is the return from submitting the bid $v_h - \delta$ when all other informed players refrain from targeting this market segment. The inequality suggests two things: (i) there is no profitable deviation to soliciting the non-distressed players, as even the best one available is not sufficient, and (ii) by continuity, we can find: $\bar{B}^I$ such that:

$$\xi(v_h - \bar{R}^d)\pi^{n-1} = v_h - (v_h - \bar{B}^I); \quad \text{and} \quad \bar{B}^I < v_h - \delta$$

Next, assume that: $\xi < \frac{\delta}{(v_h - \bar{R}^d)}$. Thus:

$$\xi(v_h - \bar{R}^d)\pi^{n-1} < v_h - (v_h - \delta)\pi^{n-1}$$

Where the RHS is the return of bidding $v_h - \delta$ (recall that informed dealers only submit bids that are higher than $v_h - \delta$). At the same time, the LHS is the return of the most profitable deviation from this equilibrium into the range in which only the distressed buy. We can see that there is no profitable deviation. From here, we can construct the complete equilibrium as usual. We can negate the existence of other equilibria in the following way. If there was an equilibrium in which some dealers were bidding below $v_h - \delta$, these bids would have won with a lower likelihood than $v_h - \delta$ and would not be accepted by non-distressed. Also, someone would always bid $\bar{R}^d$. Using the equation above, we can show the rest.

Last, let $\xi \in (\frac{\delta}{(v_h - \bar{R}^d)}, \frac{\delta}{(v_h - \bar{R}^d)\pi^{n-1}})$. Let $\bar{B}_d^I$ denote the highest bid that an informed player gives that is accepted only by distressed customers. Note that it is the lowest bid only when $v_h - \delta$ is the lowest bid. Thus:

$$(v_h - (v_h - \delta)) = \xi(v_h - \bar{B}_s^I)$$

Or:

$$\bar{B}_s^I = v_h - \frac{\delta}{\xi}$$

Now, we need to ensure that the interval $[\underline{B}_s^i, \bar{B}_s^I]$ is not empty. That is:

$$\bar{B}_s^I = v_h - \frac{\delta}{\xi} \geq \bar{R}^d$$

Which is satisfied by:

$$\xi \geq \frac{\delta}{v_h bybar R^d}$$

Also, note that trivially $\bar{B}_s^I < v_h - \delta$ as required. Thus, we can build an equilibrium in which some bids are accepted by all sellers and some only by the distressed ones.

It is plain to see that we cannot construct an equilibrium with trades only with the distressed guys since that requires that $\xi \geq \frac{\delta}{(v_h - \bar{R}^d)\pi^{n-1}}$ (see above). Similarly, we cannot construct an equilibrium in which all bids are accepted by the non-distressed as this will require $\xi < \frac{\delta}{(v_h - \bar{R}^d)}$ □

10.0.4 Proof of theorem 6.6

Proof. We know from the indifference condition that whenever an informed player bids on a high-quality asset, its expected payoff is:

$$\pi^{n-1}(v_h - \bar{R}^D)$$

The total expected payoff is the number of bids that the dealer gets to submit multiplied by the expected return from each bid, or:

$$\text{Expected profit} = \text{nm. of bids} \times \text{expected profit from bidding} = \mu_s(1-\pi)\pi^{n-1}(v_h - \bar{R}^D)$$

The total realized return is the number of trades the dealer conducted multiplied by the average spread per trade. The average spread will be denoted by: $\bar{S}^I(n)$. Note that the average spread measures the realized prices at which bonds were bought rather than the submitted bids.

From symmetry between the informed dealers, each executes $1/n$ of the trades they do as a group. To compute the total volume the group trades, note that there are two scenarios in which a customer is not trading with an informed dealer: (i) None of them submits a bid (prob. of π^n). or, (ii) the bids they submitted are below the customer reservation value. Specifically, the customer got hit by a mild liquidity shock (δ_r) while the bids are such that they appeal only to players that are in distress (shock of δ_s). The likelihood that any of these scenarios take place is:

$$\pi^n + (1-\pi^n) * (1-\xi) \sum_{k=1}^{n} \binom{n}{k} \pi^{n-k} (1-\pi)^k (F(v_h - \delta_r))^k$$

Recalling that the total measure of customers in the market is μ_s, we find that the total volume of trade facilitated by the informed is:

$$V^i(n) = \mu_s(\pi^n + (1-\pi^n) * (1-\xi) \sum_{k=1}^{n} \binom{n}{k} \pi^{n-k} (1-\pi)^k (F(v_h - \delta_r))^k)$$

Now, we can pin down the realized profit of the informed dealer:

Realized profit = measure of buys by the dealer × avg. spread earned when selling =

$$\frac{V^i(n)}{n} * \bar{S}^i(n) = (1-\pi^n - (1-\pi^n) * (1-\xi) \sum_{k=1}^{n} \binom{n}{k} \pi^{n-k} (1-\pi)^k (F(v_h - \delta_r))^k * \frac{\mu_s}{n} * \bar{S}^i(n)$$

Since there is a continuum of customers, the dealer's total expected profit from trade equals its total realized profit. Equating the two terms, we get:

$$(1-\pi^n - (1-\pi^n) * (1-\xi) \sum_{k=1}^{n} \binom{n}{k} \pi^{n-k} (1-\pi)^k (F(v_h - \delta_r))^k * \frac{\mu_s}{n} * \bar{S}^i(n) = \mu_s (1-\pi) \pi^{n-1} (v_h - \bar{R}^D)$$

Rearranging:

$$\hat{S}^i(n) = \frac{n(1-\pi)\pi^{n-1}(v_h - \bar{R}^s)}{V^i(n)}$$

Where:

$$V^i(n) = (1 - \pi^n)[1 - (1 - \xi)\sum_{k=1}^{n}\binom{n}{k}\pi^{n-k}(1-\pi)^k(F(v_h - \delta))^k]$$

Using the same logic, we find that when all bids submitted by the informed are more significant than $v_h - \delta_r$:

$$S^i(n) = \frac{n(1-\pi)\pi^{n-1}(v_h - \bar{R}_n^r)}{1 - \pi^n}$$

When all the bids it submits are below $v_h - \delta_r$:

$$S^i(n) = \frac{n(1-\pi)\pi^{n-1}(v_h - \bar{R}_n^s)}{1 - \pi^n}$$

□

11 Calibration Implementation Details

The purpose of the calibration is to examine whether the mechanism described in the paper can account for the magnitude of the differences in spreads and volume change across bonds in markets with varying levels of concentration. In this context, the calibration will also be used to address the question of why concentration presages a dramatic increase in spreads during a crisis but is correlated with a more muted difference in regular times.

I assume that a crisis implies changes in the composition of the assets traded in the market, captured by v_l, q_h, a tightening of dealers' capital constraints, embedded in π, and an increase in the demand for liquidity, manifested in a greater share of distressed customers (higher ξ). I normalize the value of good assets, v_h, to 1 in each period and am left with ten parameters:

$$v_l^g, v_l^b, q_h^g, q_h^b, \pi^b, \pi^g, \xi^g, \xi^b, \delta_r, \delta_s$$

To mitigate selection bias, I calibrate the data to a subsample of transactions in which a dealer buys from a customer bond rated "BBB-" with a par value between $1 M to 5$M. I further limit my attention to trades made by the top 50 dealers and exclude agency trades. Following

Kargar et al. (2021), I define the Covid-crisis as the period starting on March 5th, 2020, and ending on April 10th of that year. I regard the "normal" times as the pre-crisis period that starts on Jan. 1st, 2019 and ends with the onset of the Covid-19 crisis.

I begin by calibrating parameters that govern the behavior of the market in normal times, δ_r, ξ^h. For δ_r, I use the measure of Chen et al. (2018), who estimated that sellers' holding costs of bonds rated Ba in normal times are 83 bps, and those rated Baa at 67 bps. Picking the midpoint, where $BBB-$ belongs, I set $\delta_r = 0.75$. Alongside, I assume that $\xi^g = 0$. I will show below that this assumption is benign.

Next, I calibrate parameters that determine asset composition: $q_h^i, v_l^i, i \in g, b$. Recall that we interpret v_h^i as the value of a "typical" bond in a specific market, where a market consists of all bonds that have similar observable attributes. In contrast, v_l^i is the value of bonds that share those observable attributes despite being riskier. I interpret this to imply that if someone had learned its true risk value, they would have assessed it as riskier than it appears. In other words, such a bond would be downgraded conditional on being audited by a rating agency. I assume that bonds are audited at random, and hence the share of low-quality bonds, $1 - q_h$, equals the probability of being downgraded conditional on a re-rating event (downgrade, upgrade, or re-affirmation of its rating). Using the Mergent-FISD rating table, I find that in the pre-crisis period, 13% of re-rating of bonds rated "BBB-" end with a downgrade (that is - $q_h^g = 0.87$). Similarly, during the crisis, the likelihood of being downgraded increases to 18%, so that $q_h^b = 0.82$.

Similarly, I consider v_l as the expected value of a bond conditional on a downgrade. To estimate the value of a bond, I use its price in dealer-to-dealer trades. Given that dealers operate in a relatively frictionless market, the inter-dealer price of a bond should closely reflect its true value. I concentrate on small trades (less than $10,000) to avoid biases stemming from differences in holding costs across trades with varying volumes.

In the pre-crisis period, 54% of cases in which a BBB-" bond is downgraded result in an assigned rating of BB+. In the remaining 46%, the assigned rating is BB. Using these probabilities as weights, the expected value is $\nu_{dngrd,BBB-}^{pre} = 99.8$. Following a similar procedure, I find that in the crisis period $\nu_{dngrd,BBB-}^{crisis} = 0.89$. Remember that I normalized

$\upsilon_h = 1$. Consequently, υ_l is defined based on the relative value of an inferior bond when compared to a standard one. Denote the dealer-to-dealer price for BBB-" bonds in period P as ν^P_{BBB-} and note that:

$$\frac{\upsilon^g_l}{\upsilon^g_h} = \upsilon^g_l = \frac{\nu^{pre}_{dngrd,BBB-}}{\nu^{pre}_{BBB-}} = 0.997, \qquad \upsilon^c_l = \frac{\nu^{crisis}_{dngrd,BBB-}}{\nu^{crisis}_{BBB-}} = 0.89$$

Note the wide gap separating the expected fall in prices due to a downgrade during the crisis when compared to the pre-crisis period. This is not special to bond-rated "BBB-", but rather reflects a general widening between the price of bonds of different ratings in dealer-to-dealer deals during the crisis. I regard this to indicate an increase *cost of bearing idiosyncratic risk* due to the expected deterioration in market performance. As we shall immediately see, this increase in the cost of risk plays a substantial role in facilitating the impact of concentration on market performance in times of crisis.

Now, I turn to estimate the remaining four parameters: $\delta_s, \xi^c, \pi^c, \pi^g$. I determine these values by targeting the behavior of spreads in markets with varying degrees of competition. Consequently, I classify bonds into three bins: those with an HHI of 0.3-0.4, with an HHI of 0.4-0.7, and with an HHI of 0.7-1. These groups represent markets with three informed dealers, two informed dealers, and a single informed dealer, respectively. For each bin, I calculate the mean spread during the pre-crisis and crisis periods. To minimize measurement error, I use a multi-step process to estimate the mean for each period and concentration bin pair, including calculating the mean for each bond-era pair, winsorizing, and computing the mean for all bonds within each bin [8].

[8] I am gauging spreads using the O'Hara-Zhou method used in section 4. That is, for each trade, I find the percentage deviation of the price that a dealer paid for it when buying it from a customer vs. the price paid for it in the most recent dealer-to-dealer trade. To avoid bias, I limit my attention only to trades in which the trade used to calculate the reference price occurred more than an hour but less than two weeks than the time when the transaction took place. The purpose of ignoring spreads calculated using a dealer-to-dealer trade that occurred less than an hour before is to exclude agency trades that might have been wrongly categorized as principal. Alongside this, to limit the impact of outliers on my final results, I calculate the mean spread in a few steps. First, I calculate for each bond-era pair a weighted mean of the spreads charged from customers who sold it. As a weight, I used the inverse of the time that elapsed between the dealer-to-dealer trade used to gauge the reference price and the current transaction. Then, I winsowrised the bond-level weighted mean at the 10% and the 90% percentile level, with the purpose of diminishing the impact of outliers on my final result. Lastly, I take a weighted mean over all bonds in each period and concentration category, using the number of trades in the bonds as a weight.

The spreads in the data appear in Table 14. As one can see, there is a clear trend of rising spreads alongside HHI during the COVID-19 crisis. The differences between more and less competitive markets appear substantial, as a transition from a three-informed players market to a one-informed player market increases the average spread by about 70%. In contrast, in regular times, we witness an increase in spreads when transitioning from 3 informed players to 2 informed players market, but then see almost the exact same spreads for $n = 1$ and $n = 2$.

HHI	Spreads (pre-crisis)	Spreads (crisis)	Volume Change
> 0.6	24.41	169.3	-0.71
0.4-0.6	24.25	113.98	-0.33
0.3-0.4	15.37	98.80	-0.15

Table 14: Weighted mean - spreads by HHI, COVID-19 crisis and the period proceeding it

I use the six average spread moments to calibrate the four remaining parameters. Specifically, I choose parameters to minimize the percentage change deviation between the spreads in the data versus those in the model, that is:

$$\sum_{i \in \{g,c\}} \sum_{n \in \{1,2,3\}} (\frac{\hat{\bar{S}}_n^i - \bar{S}_n^i}{\bar{S}_n^i})^2 \tag{9}$$

Where $\bar{S}_n^i$ is the mean spread in state i in a market for a bond with n informed dealers in the data and $\hat{\bar{S}}_n^i$ is its model equivalent. Also, I restrict the parameter space by requiring that it will be harder to get a bid from a dealer in times of distress, that I restrict the solution space to the cases where $\pi^c > \pi^g$.

Note that this is not a convex problem, as multiple factors interact to determine the realized spreads. Their impact is often non-monotonic. For instance, an increase in π pushes spreads up by increasing informed players' monopolistic power, but may also decrease them by emboldening the uninformed to bid more aggressively and pose competition. To address the non-convexity, I search for the missing parameters using a particle swarm algorithm.

In each iteration of the algorithm, I guess the four parameters and add them to the other parameters of the model that were pinned down in earlier stages of the calibration. Then, I plug the parameters into the model to derive the average spread for each state, $i \in \{r, c\}$, and for markets with $n \in \{1, 2, 3\}$ dominant dealers. Specifically, I make use of the informed dealers' optimality condition (eq. 6) to pin down the probability of submitting a bid that appeals only to the distressed players $(F(v_h - \bar{R}^r))$, and plug in the result I attain into the realized spread equation derived in Theorem 6.6. For further details, see the appendix. Lastly, I calculate the loss function (7).

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