

Learning by Trading: The Case of the U.S. Market for Municipal Bonds*

Giulia Brancaccio,[†] Dan Li,[‡] Norman Schürhoff[§]

November 2017

[Link to the Latest Version](#)

Abstract

In markets where public information about fundamentals is limited, and trade takes place under conditions of asymmetric information, agents may rely on their trading activity to acquire information about the state of market fundamentals. Information acquisition, therefore, becomes an additional motive for trade. In this paper we use a combination of reduced-form techniques and structural analysis to characterize and measure experimentation motives for trade in the U.S. secondary market for municipal bonds. First, we provide reduced-form evidence that experimentation is a first-order motive for trade. To rationalize these facts, we design a dynamic model of trade in this market that allows for linkages between trading activity and information acquisition (i.e., experimentation). The model is estimated using detailed micro-data on trading activity on the secondary market for municipal bonds. We use the model to characterize the incentives to experiment. We find that dealers are willing to pay up to 15% of the intermediation spread to double the precision of their information about the state of fundamentals. Furthermore, we show that experimentation allows dealers to increase the precision of their estimate of the asset's value by 25%, and we characterize the process of information diffusion across agents. Finally, we find that experimentation explains up to 10% of the volume of trade in the market.

*I am deeply indebted to my advisors, Bo Honoré, Myrto Kalouptsi, and Jakub Kastl, for their continued guidance and support. For helpful comments and discussions at various stages of this project we thank Nick Buchholz, Sylvain Chassang, Jan De Loecker, Tommaso Denti, Adam Kapor, Eduardo Morales, Motohiro Yogo, Clara Santamaria, Molly Schnell, Theodore Papageorgiou, and seminar participants at Princeton University, Harvard University, and the Board of Governors of the Federal Reserve System.

[†]Princeton University, Department of Economics, Julis Romo Rabinowitz Building, Princeton, NJ 08544, USA. Email: giulia@princeton.edu

[‡]Board of Governors of the Federal Reserve System, Washington, DC 20551, USA. Email: dan.li@frb.gov

[§]University of Lausanne, Swiss Finance Institute, and CEPR. Email: norman.schuerhoff@unil.ch

1 Introduction

The desire to acquire information provides a powerful explanation for many economic phenomena. Often information is explicitly purchased by, for example, investing in market research or hiring experts. In contexts where agents learn from the consequences of their actions, the demand for information creates a trade-off between choosing the best action for today and choosing the most informative action about tomorrow: to acquire valuable information, agents might decide to deviate from the action myopically most profitable and “experiment.”

This trade-off is particularly relevant in markets where trade is decentralized. Here, the lack of a centralized trading mechanism often implies that public information about prices and volume of trade is limited. Therefore, agents must rely on their own trading activity to acquire information about the market fundamentals: negotiating with others reveals information about the counterparty’s valuation of the asset. This, in turn, provides valuable information about the overall state of the market.

In this paper, we investigate whether information acquisition is a first-order motive for trade in decentralized markets and explore the implications of experimentation for the functioning of these markets. Our setting is the secondary market for U.S. municipal bonds, a decentralized market with trades totaling over \$3 trillion per year. Two reduced-form facts reveal that information acquisition is a key driver of trading decisions for agents operating in this market. These facts motivate us to build a framework for studying information acquisition as a motive for trade. Forward-looking dealers build an inventory of an asset by trading with one another (inter-dealer trade) and with myopic investors. The investors’ valuation for the asset depends on a persistent and unobserved common preference shock. Trading is costly but reveals information about investors’ valuations, creating incentives to experiment. To quantify these incentives to experiment, we estimate the model using rich micro-level data on trading activity. The results suggest that information is valuable: we find that dealers are willing to pay up to 15% of the intermediation spread to double the precision of their information about market fundamentals. Moreover, we study the process of information diffusion in the market and find that dealers acquire information mostly by trading among themselves, rather than directly trading with investors. Finally, we find that experimentation explains up to 10% of the volume of trade in the market.

States and municipalities throughout the United States depend on the municipal bond market to raise

funds for investments in schools, highways, and other public projects. Several features of this market make it an ideal laboratory to study the interaction between trading and experimentation. First, trade in municipal bonds is decentralized, and learning about the terms of trade involves participating in trade directly. Second, a large number and variety of bonds are outstanding at any given time, and each asset includes a variety of complex special provisions. This complicates pricing and makes information acquisition a first-order issue. Finally, in recent years, the Municipal Security Rulemaking Board (MSRB)—the regulatory body for the municipal bond market—has taken a number of concrete steps to improve access to information about market activity for market participants. These changes in the information structure that agents face allow us to directly test the importance of experimentation in explaining the behavior of financial institutions active in the market.

We use a proprietary data set from the MSRB that covers the universe of transactions involving a municipal bond between 2000 and 2005. Importantly, the data contain an identifier for the dealers involved in each transaction, allowing us to construct the complete trading history for each dealer.

Two reduced-form facts illustrate the relevance of information acquisition for shaping the trading behavior of agents operating in decentralized markets. First, data on inter-dealer trade show that after a dealer sells an asset to another dealer at a particularly high price, he will increase the price he charges to his clients for the same asset. A variety of placebo tests suggest that this result is not spurious and indicates that this change in behavior is likely driven by information acquisition. Trade, therefore, can be a source of valuable information.

Second, we look at the outcome of a policy change that increased access to public information about trading activity and prices in the municipal bond market. We focus on uninsured assets where incomplete information is arguably more severe, since insurance protects investors against the risk of default. We find that the volume of trade for assets that are uninsured falls compared to insured assets. Moreover the price at which dealers are willing to buy (sell) uninsured assets decreases (increases). This suggests that information acquisition is a key incentive that prompts dealers to take on the risk of holding this type of asset in inventory.

To rationalize these facts, we build a dynamic model of trading in decentralized markets where dealers trade and experiment. Forward-looking dealers build costly inventories of municipal bond holdings by

trading with myopic retail investors and other dealers. Investors’ valuations for the asset change over time due to a persistent, common, and unobservable preference shock (the “market fundamental”). Since dealers can choose the timing of trade, their returns depend critically on the information they are able to acquire about the state of the market. Incentives to experiment enter the decision to trade: trading is costly but trading prices are informative about the unobserved shock. When facing retail investors, each trade has the same information content, but trading with more investors allows the dealer to sample more observations and it is both riskier and costlier. When trading with other dealers, trading prices are informative about the counterparty’s valuation for the asset, which in turn reveals what he knows about the state of the market. Some dealers have better information than others due to their trading history. To capture the decentralized nature of trade, we allow dealers to only observe a summary statistic of the past trading activity of their peers, which we call “experience.”

A dealer’s trading decisions depend on two unobserved objects: their information about fundamentals and their experience. In the estimation, we first use inter-dealer trading and trading history to recover the dealer’s information about the state of fundamentals and experience. Next, we use the dealer’s trading choices to recover the core set of primitives —trading costs and the cost of holding inventory.

We exploit an implication of the model to recover dealers’ experience: more experienced dealers will pay lower prices to buy assets in the inter-dealer market. Our baseline specification compares how prices for trades executed by a specific seller, in a specific month and asset, change depending on the past trading experience of the buyer. We focus on comparisons for a fixed month and seller to ensure that the estimates are robust with respect to market-wide shocks. We also consider alternative specifications to address the potential bias introduced by unobserved buyer’s heterogeneity. In particular, we use inflow and outflow of funds in the market for municipal bonds to build dealer-specific liquidity shocks and include these as instruments for the dealer’s experience.

To recover the dealers’ information about the fundamentals, we assume that dealers only acquire information through trade or through public signals accessible to everyone, the econometrician included. We exploit a Hansen-Sargan test for over-identifying restrictions to show that dealers have no information about the state of fundamentals of an asset in periods in which they did not trade the asset. This suggests that learning activities in the market for municipal bonds are strongly connected to “realized” trade and

provides a justification for this assumption.

The estimated model serves two purposes. First, we use the model to characterize the value and precision of information for dealers active in the market. We find that dealers are willing to pay up to 15% of their average intermediation spread (i.e., the difference between the price at which they buy and sell the asset) to double the precision of their estimate of the asset’s market value. Furthermore, we find that experimentation allows dealers to increase the precision of this estimate by 25%. Finally we study how information is disseminated across agents.

Second, we explore the impact of experimentation on the volume of trade in the market. We find that improving market transparency can reduce the volume of trade for an asset by more than 10% by weakening the incentives to experiment. Two effects are at play. On the one hand, transparency weakens the incentives to experiment. On the other hand, it reduces uncertainty about the state of the market fundamental. This makes dealers more confident and gives them incentives to trade larger quantities of the asset, partially offsetting the first effect. The final balance of these two forces varies dramatically depending on the assets’ underlying primitives. For this reason we perform a comparative static analysis to identify the features of the asset that will determine the success of this types of policies.

We focus on volume of trade for a number of reasons. Many authors, starting with [Pagano 1989](#), [Kyle 1985, 1989](#), and [Admati and Pfleiderer 1988](#), have argued that volume of trade is a key variable to determine whether investors can sell an asset on short notice without loss (that is, to determine whether an asset is “liquid”). Issuers, in turn, pay a high price to issue illiquid securities. As an example, [Wang et al. 2008](#) estimate that municipal bond issuers pay \$13 billion a year to compensate investors for the risks implied by the illiquidity of the market. Increasing the volume of trade in this market, therefore, can translate to huge savings for local governments and municipalities. Finally, volume of trade can be an interesting outcome variable per se, as historically it has been the target of policies addressing the inefficiencies of decentralized financial markets.

Related Literature This paper is at the intersection of three principal strands of literature. The basic trade-off between learning and sacrificing immediate payoff is focal in the literature on strategic experimentation. We empirically quantify the strength and implications of this basic trade-off in the context of decentralized financial markets. Finally, we integrate these concepts with ideas from empirical

studies of industry dynamics.

Experimentation has long been studied in economics, mostly from a theoretical standpoint (for a survey, see [Hörner and Skrzypacz 2016](#)). Several papers within this literature explicitly share our focus on experimentation as a motive for trade —most notably [Aghion et al. 1993](#), [Grossman et al. 1977](#), [Mirman et al. 1993](#), and [Kihlstrom et al. 1984](#). Our focus remains an empirical one. For this reason, we strip the incentives to experiment to their minimal components. This makes the agents’ problem tractable, allowing us to bring the model to the data.

Several papers, such as [Leach and Madhavan 1993](#) and [Bloomfield and O’Hara 1999, 2000](#), have discussed the implications of experimentation for the trading behavior of agents in financial markets. Furthermore, [Wolinsky 1990](#), as well as [Golosov et al. 2014](#), and [Blouin and Serrano 2001](#) explore the linkages between trading and information diffusion in a decentralized market with private information. Their objective is to study under what conditions all relevant information is revealed over time. Despite this interest, direct quantification of the role of experimentation and measurement of its implication for market structure has remained scarce. We contribute to this literature by employing a tractable analytical framework to empirically study the role of incentives to experiment as a motive for trade.

We integrate the literature on experimentation with a recent literature that uses search models to study the trading behavior of agents in decentralized markets. Largely, these papers build on the framework developed by [Duffie et al. 2005, 2007](#), to study search frictions in the context of these markets both in theory (most recently, [Hugonnier et al. 2014](#) and [Farboodi et al. 2016](#)) and empirically ([Gavazza 2011b,a](#)). In this paper, we focus on a different feature of decentralized markets: the lack of public information about trade activity.¹ For this reason, we borrow the most basic structure of these models and enrich it with incomplete information and learning; in our setup the decision to trade not only depends on inventory management and search costs but also on experimentation.

Finally, we relate to the literature on industry dynamics (e.g., [Hopenhayn 1992](#), [Ericson and Pakes 1995](#)) which characterizes Markov-perfect equilibria in entry, exit, and investment choices given some uncertainty in the evolution of the states of firms and their competitors. Instead of these choices, we model the agents’ problem as a series of trading and pricing decisions. Since agents interact with one another repeatedly, this problem generates a particularly high-dimensional state space. We introduce a number

¹[Duffie and Manso 2007](#) have a similar focus, but they focus on information diffusion rather than information acquisition.

of innovations to mitigate the computational burden. First, to simplify trading decisions, we assume that agents only observe a summary statistic of the trading history of other market participants. This assumption not only permits solving for equilibrium policies of agents and simplifies the agents' inference, but also reflects a more realistic behavioral model for decentralized markets. Moreover, given the large number of dealers in the market, we assume that the distribution of dealers' private states is perfectly forecastable by agents, conditional on the preference shocks they are trying to learn. This approach has precedent in the literature on firm dynamics (Weintraub et al. 2008). Finally, our empirical methodology borrows from the literature on the estimation of dynamic setups (e.g., Rust 1987, Aguirregabiria and Mira 2007, Bajari et al. 2007, and Pakes et al. 2007) in exploiting conditional choice probabilities to obtain information on the value functions and, in turn, on the primitive of interest.

The rest of the paper is structured as follows. Section 2 provides a description of the industry and the data used. Section 3 presents a number of reduced-form facts suggesting that experimentation is a first-order determinant of agent's trading decisions in the market. Section 4 describes the model. Section 5 lays out our empirical strategy, while in Section 6 we present the estimation results and characterize dealers' incentives to experiment. Section 8 discusses the implication of our results in term of market structure, while Section 9 concludes. The Appendix contains additional tables and figures, proofs to our propositions, as well as further data and estimation details.

2 Industry and Data Description

2.1 The Secondary Market for Municipal Bonds

Municipal bonds are debt securities issued by states, cities, and other local governments to fund day-to-day obligations and to finance capital projects. Their importance cannot be overstated: in 2017 they were the main source of funding for 75% of the total public investment in infrastructure.

To ease credit access for local governments, interest rates accrued on municipal bonds are exempt from individual income taxes both at the federal and the local level. Due to this obvious tax advantage, 70% of the total municipal debt outstanding is held by private investors directly (50.2%) or through mutual funds (20%).

The secondary market for municipal bonds is organized as a standard decentralized market. There is no central exchange for municipal securities, and financial institutions registered with the SEC as municipal securities broker-dealers intermediate trades among investors. Dealers execute nearly all transactions in a “principal capacity”: the dealers buy the assets directly and hold them in inventory until they are able to find a buyer. Dealers, moreover, can trade among themselves in the inter-dealer market. Every year there are more than 2,000 active broker-dealers, and the largest market share is around 10%.

At any given time there is a large number of bonds outstanding, each of which includes complex features. This lack of standardization worsens incomplete information and makes information acquisition a first-order issue. In particular, over our sample period there are 1.5 million different assets outstanding, issued by more than 50,000 different units of state and local governments.² Moreover, several types of special provisions can complicate pricing. As an example, callable bonds are redeemable by the issuer before the scheduled maturity, while a sinking fund provision requires the issuer to retire a specified portion of debt each year. Furthermore, nonstandard interest payment frequencies are not uncommon, and most of the outstanding assets have some form of credit enhancement.³ The majority of the outstanding assets have more than one of these special provisions: Harris and Piwowar 2006 show that only a small fraction of the outstanding assets (around 14%) contain no complexity features.

The lack of a centralized trade mechanism together with the lack of standardization imply that the information needed to price the assets is often not public. Yet, some coarse indexes about market activity are publicly available. In particular, since 1995, the MSRB has published information about the volume of trade and average trading price for assets traded more than four times during the previous day (“next-day reporting”). This, however, covers only 5% of the assets traded. Moreover, the most widely watched municipal bonds indexes are compiled by “*The Bond Buyer*.” These indexes are either based on dealers’ estimates for the price of a hypothetical bond⁴ or on the activity on the primary market. However, these are too coarse to effectively reduce the uncertainty for the pricing of individual bonds.

Access to public information about trade activity has improved steadily in recent years. The four-trade threshold for next-day reporting was abandoned on June 23, 2003, when all trades began to be reported

²For comparison, this is 20 times the number of corporate bond types.

³An issuer improves the credit rating of a security by purchasing the financial guarantee (e.g., insurance, letter of credit) of a large financial intermediary.

⁴This is the case for the 20-Bond Index, the 11-Bond Index, and the Revenue Bond Index.

the next day. Moreover, since January 31, 2005, information about each transaction in the market is made available online within 15 minutes of the execution of a trade. Investors seem to have embraced the new source of information with enthusiasm: on the first day of 15-minute trade reporting, The Bond Market Association reported that the website on which trades were reported averaged about 10,000 visits per minute.⁵ In Section 3 we leverage these changes to show that incentives to experiment are a first-order determinant of the volume of trade in the market.

Finally, investors' participation in the secondary market is driven by liquidity shocks rather than speculation. Municipal bonds are considered to be a relatively safe investment, with historically low default rates. As an example, for Aa- and A- rated municipal bonds, the 10-year cumulative default rate is .03% compared to 0.8% for corporate bonds. The low default risk and the composition of the owners, tend to make municipal bonds "buy-and-hold" investments. In other words, municipal bonds are mainly bought at issuance and held until maturity. For this reason, when we think of incentives to experiment we focus on dealers' incentives to trade. Consistent with this, trades on the secondary market are small: the median trade is worth \$25,000, and 80% of trades have a value of less than \$100,000.

2.2 Data

Our main data source is the proprietary Transaction Reporting System audit trail from the MSRB. In an effort to improve market transparency, the MSRB has required dealers to report all transactions in municipal securities since 1998. The transactions data cover the 5-year period from January 2000 to December 2005. For every transaction involving municipal bonds, our data provide information about the terms of the trade, such as the trading price, date and time of the trade as well as par value (the value at maturity of the asset exchanged, or the volume of the trade) of the asset, and an asset identifier. Significantly, we observe identifiers for the dealer firm intermediating each trade: for customer trades, the data identify the dealer buying and the dealer selling the bond, while for trades among dealers, the data identify the dealers on each side of the trade. In addition to the comprehensive transactions data, we obtained reference information on all municipal bonds, including issuance date, maturity, coupon, taxable status, ratings, call features, issue size, and issuer characteristics from Thomson SDC. Finally, we obtain the time series for market bond indexes, as well as monthly municipal mutual fund flows from Bloomberg.

⁵See Schultz 2012.

We filter the transactions to eliminate data errors and ensure data completeness. For a bond to be in our sample, it must have complete descriptive data in the SDC and satisfy a number of trade-specific filters and bond specific filters (fixed or zero coupon, non-derivative, non-warrant, not puttable, maturity ≥ 1 year, \$5K denomination). Since the focus of this paper is on the secondary market, we remove all trades during the first 90 days after issuance and less than one year away from maturity.⁶

Summary statistics Our final data set involves 20,207,244 trades on the secondary market between 2000 and 2005, involving 587,224 unique assets. As shown in Table 1, on average 34 million dollars worth of assets are bought or purchased by private investors every month. The average price is \$99.45, across sales and purchases, with substantial variation (the overall standard deviation is \$10.68, and the median standard deviation within each month is \$10.44). The difference between the price paid to and from investors within a month (the “intermediation spread”) is on average 2%. Consistent with the description of the market in Section 2.1, the trade size is on average \$70,000 (the median is \$25,000) and institutional size trades (above 1 million) happen sporadically (they represent 1% of the total trades).

There are 4,072 different dealers active in the market over our sample period. The largest dealer intermediates 10% of total trades, while the second largest dealer has less than a 5% market share. We obtain a similar picture if we use a narrower definition of “market”, that takes into account the possibility that dealers specialize. For instance, the highest market share by state of issuance is on average 15%.

Interaction on the inter-dealer market is sparse: the inter-dealer trade is one-third that of trade with investors. Finally, dealers’ trade relationships do not seem to be very persistent. As can be seen in the last row of Table 1, on average (across dealers) every second transaction on the inter-dealer market involves a new counterparty.

⁶As a result of these filters, we retain 65% of all the transactions included in the initial dataset.

Table 1: Summary statistics

	Mean	St. Dev	Median	Min	Max
Trading Price	99.484	10.68	101.52	36.644	116
Intermediation spread	2.1	1.55	1.19	-0.23	6.8
Monthly trade to investors (10^7 USD)	3.45	0.51	3.38	2.35	4.85
Monthly inter-dealer trade (10^7 USD)	1.50	0.25	1.48	1.02	2.25
Trade size (1,000 USD)	72.05	190.92	25	5	2,245
Dealers' market share	0.043	0.40	0.00026	2^{-7}	11.6
Inter-dealer trades with a new counterparty (%)	44.49	37.63	30.66	0.07	1

Notes: The above table provides summary statistics for trading activity on the secondary market for municipal bonds US. Data come from the proprietary Transaction Reporting System audit trail from the MSRB, and covers the universe of transaction in this market between 2000 and 2005.

3 Reduced-Form Evidence

In this section, we present reduced-form evidence that suggests that: (i) dealers acquire information through trade; and (ii) dynamic incentives to acquire information are an important determinant of dealers trading and pricing behavior.

3.1 Learning Through Inter-Dealer Trade

In markets where public information about trading activity is limited, agents need to rely on private interactions with other agents to aggregate the information dispersed in the market. In particular, negotiating with others can reveal information about the counterparty's valuation for the asset. This, in turn, provides valuable information about the overall state of the market.

We use data on inter-dealer trade to argue that dealers do extract information from prices in inter-dealer trades and change their trading behavior to account for this information. This suggests that bargaining, and trade in general, can be a source of valuable information for market participants.

We consider the situation depicted in Figure 1. In particular, consider a dealer s who sells an asset to a dealer b at price $q_{s \rightarrow b}$. Suppose that price $q_{s \rightarrow b}$ is higher than the average price that dealer s was

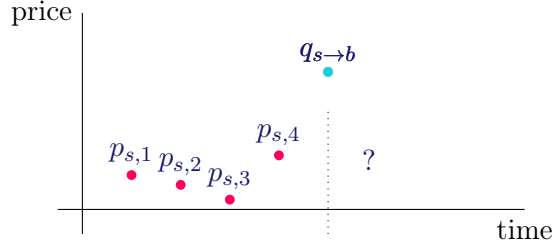


Figure 1: Experiment

charging to his clients in the previous week, $(p_{s,1}, \dots, p_{s,4})$. Seller s could interpret price $q_{s \rightarrow b}$ as a signal that the asset is more valuable than he thought. In this case, one might expect that he will revise his pricing strategy and increase the price he charges to his clients.

Concretely, let i denote a generic inter-dealer trade, for asset a_i at price q_i ⁷. Moreover, s_i and b_i , denote, respectively, seller and buyer involved in trade i . Similarly, let j denote a generic *sale* to an investor, executed by dealer s_j , at price p_j . For every inter-dealer trade i we construct the average price charged by seller s_i , for asset a_i , to his clients in the two weeks preceding (or following) the trade, $\hat{p}_i^{\text{before}}$ (or \hat{p}_i^{after}), as

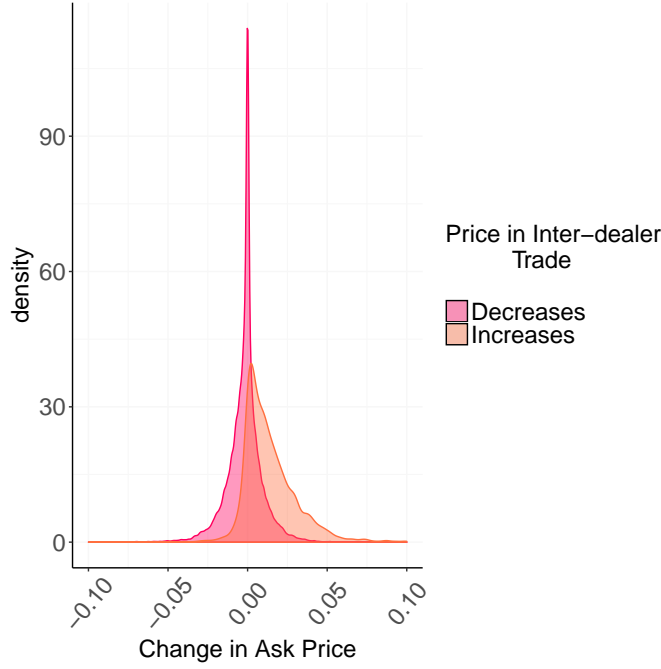
$$\hat{p}_i^{\text{before}} = \frac{\sum_{j \geq 1} p_j \mathbb{I}\{-2 \leq \text{week}_j - \text{week}_i < 0, a_i = a_j, s_i = s_j\}}{\sum_{j \geq 1} \mathbb{I}\{-2 \leq \text{week}_j - \text{week}_i < 0, a_i = a_j, s_i = s_j\}}.$$

We summarize the change in dealer s_i pricing behavior after trade i with the quantity $\Delta_i = \frac{\hat{p}_i^{\text{after}} - \hat{p}_i^{\text{before}}}{\hat{p}_i^{\text{before}}}$. The orange density in Figure 2 plots differences Δ_i for all those trades i for which $\hat{p}_i^{\text{before}} < q_i$. Remarkably, after 87% of such trades, dealer s_i increases the price he is charging to his (non-dealer) clients. On average, prices change by 1%, and this average change is significant at the 5% level. The second density in Figure 2 shows the differences Δ_i for all those trades i for which $\hat{p}_i^{\text{before}} > q_i$. Remarkably, in this case, only 55% of the prices increase, and the change is not significant.

Figure 3 plots the results of two different placebo tests to verify that this result is not spurious. First, one might worry that the result in 2 captures liquidity shocks that lead sellers s_i to increase prices charged both to other dealers and to private investors. In this case, one would expect that the dealer will also increase the prices charged for other assets, not necessarily traded on the inter-dealer market. For this

⁷Here and throughout the paper, q denotes the price on the inter-dealer market.

Figure 2: Change in pricing behavior after inter-dealer trade



Notes: the above figure plots the histogram of the difference of the average price charged by dealers to retail investors before and after inter-dealer trades. The orange density considers trades in which average price $\hat{p}_i^{\text{before}}$ is lower than inter-dealer trading price q_i . Instead, the second density consider trades of the type described in Fig 1.

reason, we check whether the sellers s_i involved in the trades in Figure 2 also change the prices they are charging for assets that they have not traded in the inter-dealer market. In particular, for every inter-dealer trade i considered in Figure 2 we construct

$$p_{\text{placebo liq},i}^{\text{before}} = \frac{\sum_{j \geq 1} p_j \mathbb{I}\{-2 \leq \text{week}_j - \text{week}_i < 0, a_i \neq a_j, s_i = s_j\}}{\sum_{j \geq 1} \mathbb{I}\{-2 \leq \text{week}_j - \text{week}_i < 0, a_i \neq a_j, s_i = s_j\}}.$$

The right panel of Figure 3 plots the difference $\Delta_{\text{placebo liq},i} = \frac{p_{\text{placebo liq},i}^{\text{after}} - p_{\text{placebo liq},i}^{\text{before}}}{p_{\text{placebo liq},i}^{\text{before}}}$ for all the trades i included in Figure 2. In this case, only 50% of the prices increase and the average change is not significantly different from zero.

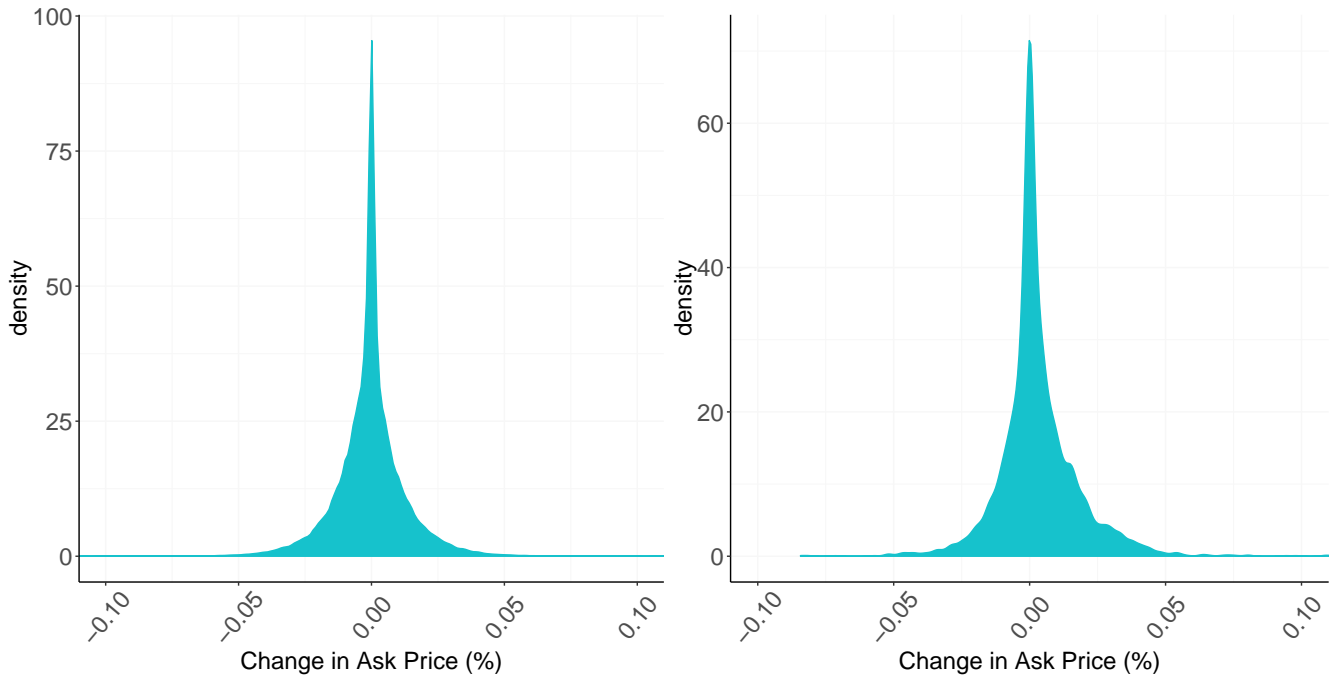
In the same fashion, one might worry that the change in behavior captured by Figure 2 is driven by a market-wide shock to the value of asset a_i . If this were true, one would expect that also dealers not participating in inter-dealer trades will change the price they are charging for asset a_i . To verify whether

this is the case, we construct

$$p_{\text{placebo mkt},i}^{\text{before}} = \frac{\sum_{j \geq 1} p_j \mathbb{I}\{-2 \leq \text{week}_j - \text{week}_i < 0, a_i = a_j, s_i \neq s_j\}}{\sum_{j \geq 1} \mathbb{I}\{-2 \leq \text{week}_j - \text{week}_i < 0, a_i = a_j, s_i \neq s_j\}}.$$

The left panel of Figure 3 plots the difference $\Delta_{\text{placebo mkt},i} = \frac{p_{\text{placebo mkt},i}^{\text{before}} - p_{\text{placebo mkt},i}^{\text{before}}}{p_{\text{placebo mkt},i}^{\text{before}}}$ for all the trades i included in Figure 2. Once again, only 48% of the prices increase, and the average change is not significantly different from zero.

Figure 3: Placebo tests



Notes: the above figure plots the results of two different placebo tests. To test whether the result is driven by dealer-specific liquidity shocks, in the right panel we plot changes in the seller's pricing behavior for assets not traded on the inter-dealer market. To test whether the result is driven by asset-specific demand shocks, in the left panel we plot changes in pricing behavior for dealers not participating to inter-dealer trades.

3.2 Improvement in Market Transparency

For years the SEC has been warning private investors and Congress about the need to improve access to information about trade activity in the market for municipal bonds. This pressure from the SEC culminated in a series of provisions aimed at improving market transparency. In particular, on June 23,

2003, the MSRB started distributing daily summaries about the trading activity in the market during the previous day. Moreover, starting on January 31, 2005, the MSRB mandated that details of all transactions in U.S. municipal bonds be reported on a timely basis and posted online almost immediately.⁸

Proponents of market transparency argue that the lack of public information about trading activity gives dealers an informational advantage. Dealers, the argument goes, exploit this advantage to extract rents from their clients by “selling high and buying low”. Market transparency, by leveling the playing field, would increase investors’ participation and benefit the market at large. For instance, SEC commissioner Arthur Levitt remarked, “The undeniable truth is that transparency helps investors make better decisions, and it increases confidence in the fairness of the markets. And, that means more efficient markets, more trading, more market liquidity.”⁹

This argument, however, ignores *dealers’* incentives to trade. Information acquisition motives for trade, in particular, can substantially erode the positive effects of transparency. Indeed, when public information about market activity is limited, trading with investors allows dealers to acquire valuable information about the market value of the asset. This generates an additional motive for trade that market transparency might weaken. Therefore, if information acquisition is a key determinant of trading and pricing decisions for financial intermediaries, improving access to public information might result in a decrease of trading activity, as well as a worsening of trading prices for investors.

We explore the effect of the 2003 policy change through a difference-in-difference set-up. We leverage the idea that improving transparency will have stronger consequences for assets for which incomplete information is more severe. A typical example of these assets in the market for municipal bonds are uninsured assets. Issuers that meet certain credit criteria can purchase municipal bond insurance policies from large private insurance companies. The insurance guarantees the payment of principal and interest on a bond issue if the issuer defaults. Pricing for insured assets, therefore, is more straightforward compared to pricing for the uninsured ones and depends less on unobserved factors.

We focus on two main outcome variables. First, we look at the response of trading activity, which we measure as the number of bonds traded times the par value exchanged in each trade (i.e. the value at maturity of the asset exchanged). Next, we look at the impact of information dissemination on the trading

⁸Asquith et al. 2013 study the effect of a similar policy intervention in the market for corporate bonds, and find similar results.

⁹Speech before the Bond Market Association.

conditions for investors. In particular, we focus on the difference between the average ask and bid price within a week (the “intermediation spread”). From an investor’s standpoint, the intermediation spread represents the out-of-pocket transaction costs of trading an asset. Instead, from a dealer’s standpoint, it affects the incentive to participate in trade.

We estimate Equation

$$y_{it} = \gamma_{0,i} + \gamma_1 t + \gamma_2 \mathbb{I}\{t > t_0\} + \gamma_3 x_i t + \lambda x_i \mathbb{I}\{t > t_0\} + \epsilon_{it}, \quad (1)$$

where y_{it} is issue i ’s outcome on week t , t_0 is the week in which the policy change is implemented, $\gamma_{0,i}$ is an indicator for bond i , and x_i is an indicator for whether the asset is uninsured. In Equation 1, any pre-existing difference between assets is captured by $\gamma_{0,i}$, while the effects of the policy that accrue to all bonds are absorbed by coefficient γ_2 . The coefficient of interest is λ , which estimates the effect of transparency on trading outcomes for uninsured assets. Finally parameter γ_3 absorbs any potential pre-existing trend for uninsured assets.

Table 2 reports estimates of the parameters in Equation 1 for different outcomes and time windows.

First, we focus on the effect of the policy on volume of trade. The estimate of the effect of the introduction of transparency on uninsured assets is negative and significant. The volume of trade for uninsured assets drops by 2.8% compared to insured assets in the 6-month window around dissemination, which is significant at the 1% level.

Next, we turn to the intermediation spread. The estimates in the second half of Table 2 show that the intermediation spread for uninsured assets increases compared to insured assets. This pattern reinforces the conclusion that the decrease in volume of trade depends on the weakening of information acquisition motives for trade and suggests that a key incentive for dealers to trade these assets is information acquisition.¹⁰

It is worth emphasizing that the estimates presented in Table 2 provide reduced form evidence that experimentation motives to trade are key. However, reduced form approaches cannot control for changes in the behavior of investors and, therefore, are not sufficient to directly measure the impact of market

¹⁰In Appendix A we show that mean trade size doesn’t change for uninsured assets as a result of the increase in transparency. This suggests that adverse selection is not the key determinant of the change in intermediation spread and volume of trade.

Table 2: Difference-in-difference estimates

	Volume of Trade (log)			Intermediation Spread		
	6 Months	9 Months	12 Months	6 Months	9 Months	12 Months
uninsured * $\mathbb{I}\{t > t_0\}$	-0.028*** (0.010)	-0.025*** (0.008)	-0.021*** (0.008)	0.020*** (0.007)	0.020** (0.008)	0.020*** (0.007)
N	1,438,297	2,142,769	2,847,241	228,741	335,994	451,482
Level	Issuer-Week					

*** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.1$

Notes: The above table presents the output from the difference-in-difference regression that measures the effect of the change in market transparency on trading activity (first three columns) and intermediation spreads (last three columns). We use insured assets as control group. Observations are at the asset-week level, and standard errors are clustered at the asset level.

transparency on dealer’s incentives to trade. In Section 8 we leverage our model to isolate the effect of market transparency on volume of trade through its impact on incentives to experiment. This not only allows us to quantify the role of experimentation but also to identify the possibly opposing channels through which incentives to experiment affect dealers’ incentives to trade. Looking at how the model primitives shape this different channels, makes it possible to identify the critical features that determine the success of the policy for a specific class of assets.

4 Model

In this section, we introduce a tractable dynamic model of trade in decentralized markets. Our goal is to capture dealers’ incentive to experiment. We begin by describing agents’ characteristics and objectives, as well as the interaction between trade and experimentation. In Section 4.2 we study players’ dynamic choice problem.

4.1 Environment

Time $t \in \{1, 2, \dots\}$ is discrete and a unique asset is traded. The market is populated by two types of agents: short-run investors and long-run dealers. Everyone is risk neutral.

Investors are myopic and live only for one period. Each investor is either a buyer or a seller. His valuation for the asset depends on an idiosyncratic component and a common preference shock $\theta_t \in \Theta$. Common shock θ_t represents common factors that affect investors' willingness to pay for the asset, and it is unobserved by investors and dealers alike. Each investor knows his own valuation but doesn't understand its correlation with other investors' valuations.

Common shock θ_t evolves over time according to a discrete Markov chain; denote by $h(\theta_t|\theta_{t-1})$ the probability of moving from state θ_{t-1} to θ_t . Publicly available information about the common shock is summarized by public signal y_t^P observed in each period t with mean θ_{t-1} . In the context of the market municipal bonds, this public signal captures information contained in monthly indexes about the market performance, as well as information about the performance of municipal mutual funds.

Dealers $d \in \{1, \dots, D\}$ are forward-looking players with time preferences determined by a constant discount rate $\beta > 0$. In every period, dealers can trade the asset with investors and among themselves. Assets bought and not sold accumulate over time and form inventory $x_{d,t} \in \{0, 1, \dots\}$. Due to the illiquidity of the market for municipal bonds, short selling is rare and costly. For this reason, we assume that short selling is infeasible. Therefore inventory is always positive. Carrying inventory is costly: in every period dealers pay a cost $\kappa(x_{d,t}) \geq 0$. Inventory cost $\kappa(\cdot)$ captures frictions that prevent dealers to increase balance sheet size, such as the cost of capital (usually inventory is levered) or limits to exposure to risk. The only source of revenue for the dealers is the resale price of the asset, while operating costs depend on the price paid to buy the assets and costs required to carry out trades.

Over time dealers form beliefs about the common shock. We denote by $\pi_{d,t} \in \Delta(\Theta)$ the probability that dealer d assigns to different values of θ_t given the information he has accumulated before time t .

We begin describing the trading protocol for trade with investors. Then we describe then we detail the trading protocol for inter-dealer trade.

Trade with Investors. In every period t , each dealer d decides whether to buy or sell (or do nothing) the asset to investors and how many investors to search for and trade with. We focus on the dealers' role in inter-temporal intermediation, rather than cross-sectional intermediation. For this reason we assume that dealers cannot both buy and sell the asset to investors in each period. This assumption is natural in the market of municipal bonds, where for only 7% of dealer-month-issuer pairs we observe a “comparable”¹¹ amount of sales and purchases. In each trade only one unit of the asset is exchanged.

Denote by $n_{d,t} \in \{-x_{d,t}, \dots, N\}$ the number of units of the asset the dealer trades with investors. The lower bound $n_{d,t} \geq -x_{d,t}$ comes from the assumption of no short sales. The upper bound is for notational convenience.¹²

Trading with investors is costly. The cost of trading captures separately factors that affect the dealer's decision on whether to buy or sell the asset, and on how many units of the asset to trade. Let $(\epsilon_{d,t}^{\text{buy}}, \epsilon_{d,t}^{\emptyset}, \epsilon_{d,t}^{\text{sell}}) \in \mathbb{R}^3$ be a cost shock i.i.d. over time and across dealers. For trading $n_{d,t}$ units of the asset dealer d pays a fixed cost $c_F(n_{d,t}, \epsilon_{d,t})$ depending on whether he buys or sells the asset: given cost parameters $c^{\text{buy}}, c^{\text{sell}} \in \mathbb{R}$,

$$c_F(n_{d,t}, \epsilon_{d,t}^{\text{buy}}, \epsilon_{d,t}^{\emptyset}, \epsilon_{d,t}^{\text{sell}}) = (c^{\text{buy}} + \epsilon_{d,t}^{\text{buy}}) \mathbb{I}_{n_{d,t} > 0} + \epsilon_{d,t}^{\emptyset} \mathbb{I}_{n_{d,t} = 0} + (c^{\text{sell}} + \epsilon_{d,t}^{\text{sell}}) \mathbb{I}_{n_{d,t} < 0}.$$

Parameters c^{buy} and c^{sell} can be negative to capture fees that the dealer might demand from his clients. Furthermore, let $\epsilon_{d,t}^1 \in \mathbb{R}$ be a cost shock i.i.d. over time and across dealers, the dealer also pays a search cost $c_V(n_{d,t}, \epsilon_{d,t}^1)$ to find investors interested in trading: given $c_1, c_2 \geq 0$,

$$c_V(n_{d,t}, \epsilon_{d,t}^1) = c_1 |n_{d,t}| + c_2 (n_{d,t} \cdot n_{d,t}) + \epsilon_{d,t}^1 |n_{d,t}|.$$

Letting $\epsilon_{d,t} = (\epsilon_{d,t}^{\text{buy}}, \epsilon_{d,t}^{\emptyset}, \epsilon_{d,t}^{\text{sell}}, \epsilon_{d,t}^1)$, the overall trading cost is $c(n_{d,t}, \epsilon_{d,t}) = c_F(n_{d,t}, \epsilon_{d,t}^{\text{buy}}, \epsilon_{d,t}^{\emptyset}, \epsilon_{d,t}^{\text{sell}}) + c_V(n_{d,t}, \epsilon_{d,t}^1)$.

The price $p_{i,d,t} \geq 0$ received or paid by dealer d in each trade with investors $i \in \{1, \dots, |n_{d,t}|\}$ is the outcome of a bargaining process between dealers and investors. We abstract away from the specifics of

¹¹That is, for 7% of triplets composed by a dealer d , month t and issuer a , it is $\frac{\max\{\text{sales}_{a,d,t}, \text{purchases}_{a,d,t}\}}{\text{sales}_{a,d,t} + \text{purchases}_{a,d,t}} < 0.75$.

¹²Since cost of trade is convex, this assumption is without loss of generality.

this bargaining process and capture its outcome in a reduced form way: trading prices are i.i.d. draws from a distribution $f(\cdot|\theta_t, \text{sign}(n_{d,t}))$ which depends on the current realization of the unobserved state, θ_t , and on whether the dealer is buying or selling, $\text{sign}(n_{d,t})$.¹³ This modeling approach allows us to specify the relevant variable for experimentation —prices’ informational content— in a parsimonious way.¹⁴

In sum, given cost shock $\epsilon_{d,t}$ and trading prices $(p_{i,d,t})_{i=1}^{n_{d,t}}$, the payoff from trading $n_{d,t}$ units of the asset is

$$c(n_{d,t}, \epsilon_{d,t}) - \text{sign}(n_{d,t}) \sum_{i=1}^{|n_{d,t}|} p_{i,d,t}.$$

Experimentation enters the decision of how many units of the asset to trade, since trading prices are noisy signals about θ_t . In particular, observing the trading prices allows the dealer to acquire information about the state of the market. This information is valuable, since it allows the dealer to anticipate changes in the resale value for the asset and, therefore, to improve the future timing of his trading decisions. In Section 4.2 we describe more in detail how dealers update after trading with investors.

Trade with dealers. After trading with investors, dealers can trade with one another. Inter-dealer trade proceeds as follows. A constant share α of the dealers is randomly selected to be “potential sellers.”¹⁵ Each potential seller d can make a take-it-or-leave-it offer, $q_{d,t} \geq 0$, to trade one unit of the asset. In contrast with the random search literature, the offer from potential sellers is directed to a specific dealer \tilde{d} on the other side of the market, a “potential buyer.” We allow dealers to exchange only one unit of the asset in the context of inter-dealer trade. Indeed, we capture the dealers’ decision on the extensive margin of trade in the context of trade with investors, since inter-dealer trade represents one-third of total volume trade.

Potential buyers can either accept one of the offers received or reject them all. This assumption is rarely binding for the market for municipal bonds since, conditional on participating to inter-dealer, for 80% of dealer-month pairs we see the dealer buying assets from only one counterparty. Making an offer

¹³ $\text{sign}(n_{d,t})$ equals 1 if $n_{d,t} > 0$, it equals -1 if $n_{d,t} < 0$, and it is 0 otherwise.

¹⁴An alternative way to think about this modeling choice is that, consistent with Green et al. 2010, we are assuming that dealers have strong market power vis-a’-vis retail investors. Under these circumstances dealers are able to extract all the surplus when trading with an investor and the trading price coincides with the investor’s valuation.

¹⁵The role of α is similar to that of the number of potential entrants, as it defines an upper bound on the total volume of trade in the market. The total quantity traded in the inter-dealer market remains endogenous since dealers can decide not to engage in trade, and buyers can reject the offer received.

is costly: $c^{d2d}(\tilde{d}, \xi_{d,t})$ is the cost of making an offer to dealer \tilde{d} given i.i.d. cost shock $\xi_{d,t}$. This shock accounts for idiosyncratic reasons that might lead a dealer to favor one counterparty over another. For example, the dealer might find the line occupied. Accepting the offer costs nothing.¹⁶

After a pair of dealers d and \tilde{d} have traded, they exchange information on what they know about θ_t . We model this as follows: Dealer d observes a (possibly noisy) signal $y_{\tilde{d},t}$ of dealer \tilde{d} 's current belief $\hat{\pi}_{\tilde{d},t} \in \Delta(\Theta)$ about θ_t . Belief $\hat{\pi}_{\tilde{d},t}$ is simply $\pi_{\tilde{d},t}$ updated after the trades with investors.¹⁷ We don't model the dealers' strategic decision about the information to reveal. This approximation is reasonable since the communication happens *after* trade and since we are working under the assumption that the market is large, and therefore the probability that dealers will interact again in the future is small.¹⁸

In the inter-dealer market, each dealer d is characterized by his level of *experience* $e_{d,t} \in \{1, \dots, E\}$, a publicly observed summary statistic of his history of trades up to time t . Experience is a proxy for the precision of each dealer's information about common shock θ_t . Dealers accumulate experience by trading with retail investors and more experienced counterparties in the inter-dealer market. Denote by

$$r(e_{d,t} | n_{d,t-1}, e_{\tilde{d},t-1}, e_{d,t-1}) \tag{2}$$

the probability that dealer d has experience $e_{d,t}$ given that in the previous period he had experience $e_{d,t-1}$, then traded with $n_{d,t-1}$ investors and with dealer \tilde{d} of experience $e_{\tilde{d},t-1}$. Given past history, experiences are drawn independently across dealers. We also assume that all levels of experience are recurrent; this is consistent with the idea that experience may depreciate over time. Finally, r is increasing (with respect to first order stochastic dominance) in its arguments; this captures the idea that dealers with a richer trading history have more precise information about common shock θ_t .

Experience is the main determinant of trading decisions in the inter-dealer market. Dealers are ex-ante homogeneous and differences in valuation for the asset and in information about θ_t emerge over time only because of differences in trading history. For this reason, potential sellers choose whom to trade with on the basis of what they know about the past trading activity of their peers —dealers who have been

¹⁶We cannot estimate separately the cost born by the buyer and the seller, since the resulting probability of trade depends on jointly on both. However, we also estimate the model assuming that the buyer makes the offer (and pays the cost) to the seller. The results are similar.

¹⁷After trade with investors, dealers update their beliefs according to Bayesian updating. See Section 4.2 for the details.

¹⁸Duffie and Manso 2007 adopts a similar model for how information is exchanged.

trading more will have more precise information about common shock θ_t . However, assuming that the entire past history of trades is commonly known would be not only computationally cumbersome, but also unrealistic given the opacity of the market for municipal bonds. A public summary static like experience is a parsimonious solution to these issues. In Section 5 we describe how we define dealers' experience in the data.

Beyond experience, inter-dealer trade is “*anonymous*”: dealers do not keep track of the identity of their trading counterparties. This assumption is natural since in the market for municipal bonds interaction on the inter-dealer market is sparse.¹⁹ Consistently, we assume that the cost to make an offer only depends on the experience of the recipient, and not on his identity. If dealer \tilde{d} and $\tilde{\tilde{d}}$ have the same level of experience, then

$$c^{\text{d2d}}(\tilde{d}, \xi_{d,t}) = c^{\text{d2d}}(\tilde{\tilde{d}}, \xi_{d,t}).$$

More specifically, potential seller d observes i.i.d. cost shocks $\xi_{d,t} = (\xi_{d,t}^{\tilde{e}}, \xi_{d,t}^0) \in \mathbb{R}^{\bar{E}+1}$ and pays cost $c^{\text{d2d}}(\tilde{e}) + \xi_{d,t}^{\tilde{e}}$ to make an offer to a dealer with experience \tilde{e} , and $\xi_{d,t}^0$ if he decides not to trade.

By trading with one another, dealers acquire information about one another's information about θ_t : this is another way to experiment. Both the offer received by potential buyers and the reply received by potential sellers, as well as post-trade communication, convey information about what the counterparty knows about θ_t . To avoid the infinite regress problem of learning what others know what others know..., we make the following simplifying assumption. Borrowing from the literature on social learning,²⁰ we assume that each dealer behaves as if the information received from any other dealer \tilde{d} is *independent* of what he already knew, conditional on the realization of state θ_t and the dealer's experience, $e_{\tilde{d},t}$. This is a reasonable assumption in the context of a large market where dealers share a common history of trades with very low probability.

Finally, we assume that potential buyers and sellers only update their beliefs based on *realized trade*.

¹⁹In the market for municipal bonds, the median number of interaction between two dealers, conditional on them interacting at all, is 3.

²⁰It is standard in the social learning literature to assume that agents learn through DeGroot rules of thumb models, which often involve double-counting information. Most notably, [Ellison and Fudenberg 1993, 1995](#) are benchmarks for the rule of thumb learning models. Moreover [Chandrasekhar et al. 2012](#) exploit an experimental setup to argue that a DeGroot rule of thumb model of learning might provide a better description of agents learning on a network, compared to standard bayesian updating.

This assumption is driven mainly by empirical concerns. Our data does not show offers to sell the asset that were rejected by the buyer, and therefore we cannot identify changes in dealers’ beliefs that derive from offers to trade that were rejected. This assumption is consistent with anecdotal evidence which suggests that there are strong reputational concerns involved in soliciting quotes only for their informational content, without the actual intention to buy or sell the asset. Moreover, in Appendix B we use an Hansen-Sargan test for over-identifying restrictions to show the results of a test suggesting that learning activities in the market for municipal bonds are strongly connected to “realized” trade. This suggests that the empirical bite of this assumption is limited.

Timing. To summarize, in each period the timing is as follows:

1. θ_t is realized. Dealers observe public signal y_t^P about last period’s shock θ_{t-1} . Then, they update their beliefs both to account for y_t^P and to account for the evolution of θ from the last period, according to h . Finally each dealer d pays a cost which depends on accumulated inventory $x_{d,t}$;
2. Dealers can trade with investors. Each dealer draws i.i.d cost shocks $\epsilon_{d,t} = (\epsilon_{d,t}^{\text{buy}}, \epsilon_{d,t}^{\text{sell}}, \epsilon_{d,t}^{\emptyset}, \epsilon_{d,t}^1)$ and decides with how many investors $n_{d,t} \in \{-x_{d,t}, \dots, N\}$, if any, to trade with. Trading prices are i.i.d draws from a distribution $f(\cdot | \theta_t, \text{sign}(n_{d,t}))$, which depends on the current value of the common preference shock θ_t . Dealers interpret prices as noisy signals about θ_t .
3. Dealers can trade with one another. The population is randomly divided among potential buyers and sellers. Potential sellers can make a t.i.o.l.i offer to a potential buyer to buy one unit of the asset, and potential buyers can either accept one of the offers received or reject all of them. After trade, dealers exchange information on what they know about θ_t .

4.2 Behavior

We first spell out the updating rules that dealers use to incorporate information obtained in the context of trade. Next, we derive the optimal behavior of dealers, as well as equilibrium prices. Where it does not generate confusion, we drop the d subscript and use “tilde” to denote state variables of dealer d ’s trading counterparty. For instance we use \tilde{e} instead of $e_{\tilde{d}}$ to denote the experience of dealer d ’s trading counterparty, \tilde{d} .

In this paper, we focus on a steady state of the model such that: (i) the fraction of dealers with a given inventory, belief, and experience depend on θ but not time; and (ii) the fraction of dealers with a given experience is constant in θ and time. This assumption is natural in the market at hand, where more than 2,000 dealers are active and each of them intermediates less than 10% of the total trade. For this reason, below we drop the dependence of value functions and choice probabilities on the vector e_t .

Updating Dealers first acquire information about common shock θ_t from prices in trades with investors. Dealer d , after observing prices $\vec{p}_{n,t} = (p_{i,t})_{i=1}^{|n|}$ updates according to standard Bayesian updating:

$$\hat{\pi}_{d,t} \left(\theta_t = \theta^k | \vec{p}_{n,t} \right) = \frac{f \left(\vec{p}_{n,t} | \theta^k, \text{sign}(n) \right) \pi_{d,t} \left(\theta^k \right)}{\sum_{\theta} f \left(\vec{p}_{n,t} | \theta, \text{sign}(n) \right) \pi_{d,t} \left(\theta \right)} := \mathcal{L}_{inv} \left(\pi_{d,t}; \vec{p}_{n,t} \right). \quad (3)$$

Dealers also acquire information about common shock θ_t by interacting on the inter-dealer market. Each pair of dealers d and \tilde{d} involved in a trade, first observe the action of their counterparty, and then observe signal y . The inference dealers draw from these depends on their conjecture about the counterparty's private history, conditional on common shock θ_t . The assumption of *independence* implies that dealer d 's conjecture does not depend on his own private state. The assumption of *anonymity* implies that this conjecture does not depend on the identity of the counterparty.

Denote $f^* (\tilde{y}, \tilde{q}, \tilde{e} | e, \theta)$ dealers' conjecture about the probability that a dealer with experience level \tilde{e} will make offer \tilde{q} and communicate signal \tilde{y} to a dealer with experience level e , conditional on common shock θ . Symmetrically, $f^* (y, \text{accept} | \tilde{e}, q, e, \theta)$ denotes dealers conjecture about the probability that a dealer with experience \tilde{e} will accept offer q and communicate signal y to a dealer with experience e , conditional on state θ . Seller d , with beliefs $\hat{\pi}_{d,t}$, after trading with buyer \tilde{d} updates according to

$$\hat{\hat{\pi}}_{d,t} \left(\theta_t = \theta^k | y_{\tilde{d},t}, e_{\tilde{d},t}, q_{d,t}, e_{d,t} \right) = \frac{f^* \left(y_{\tilde{d},t}, \text{accept} | e_{\tilde{d},t}, q_{d,t}, e_{d,t}, \theta^k \right) \hat{\pi}_{d,t} \left(\theta^k \right)}{\sum_{\theta} f^* \left(y_{\tilde{d},t}, \text{accept} | e_{\tilde{d},t}, q_{d,t}, e_{d,t}, \theta \right) \hat{\pi}_{d,t} \left(\theta \right)} := \mathcal{L}_{sell} \left(\pi_{d,t}; y_{\tilde{d},t}, e_{\tilde{d},t}, q_{d,t}, e_{d,t} \right). \quad (4)$$

Buyer \tilde{d} , instead, updates according to

$$\hat{\pi}_{\tilde{d},t}(\theta_t = \theta^k | y_{d,t}, q_{d,t}, e_{d,t}, e_{\tilde{d},t}) = \frac{f^*(y_{d,t}, q_{d,t}, e_{d,t} | e_{\tilde{d},t}, \theta^k) \hat{\pi}_{\tilde{d},t}(\theta^k)}{\sum_{\theta} f^*(y_{d,t}, q_{d,t}, e_{d,t} | e_{\tilde{d},t}, \theta) \hat{\pi}_{\tilde{d},t}(\theta)} := \mathcal{L}_{\text{buy}}(\hat{\pi}_{\tilde{d},t}; y_{d,t}, q_{d,t}, e_{d,t}, e_{\tilde{d},t}). \quad (5)$$

Note that since transition matrix r is increasing in past trading activity, more experienced dealers have more information about common shock θ_t . Therefore, signal $y_{d,t}$ communicated by more experienced dealers will be (possibly weakly) more informative than that communicated by dealers with lower experience level. This is consistent with the interpretation of experience as a proxy for the dealers' precision of information about common shock θ_t .

Trade with investors Let $V(\pi, x, e, \epsilon)$ be the value at the beginning of the period for a dealer who observes cost shock ϵ and has private history (π, x, e) . Then V satisfies

$$V(\pi, x, e, \epsilon) = -\kappa(x) + \max_{n \in \{-x, \dots, N\}} \left\{ -c(n, \epsilon) - \text{sign}(n) \mathbb{E} \left(\sum_{i=1}^{|n|} p_{it} | \pi, \text{sign}(n) \right) + \mathbb{E} [W(\mathcal{L}_{inv}(\pi, \vec{p}_n), x'(n; x), e, n)] \right\}. \quad (6)$$

At the beginning of the period, the dealer pays a cost that depends on the inventory owned $\kappa(x) \geq 0$, and decides how many investors n to search for. Trading prices vis-a-vis investors depend on the type of trade (sale or purchase), as well as on the unobserved asset's value θ . Not knowing θ , the dealer forms expectations

$$\mathbb{E} \left(\sum_{i=1}^{|n|} p_{it} | \pi, \text{sign}(n) \right) = \sum_{\theta \in \Theta} \pi(\theta) \sum_{i=1}^{|n|} \int p_i f(p_i | \theta, \text{sign}(n)) dp_i.$$

The dealer's private state changes after trading. In particular, the dealer's beliefs about the current value of θ evolves according to updating rule 3, while his inventory evolves according to $x'(n; x) = x + n$. Finally, the dealer moves on to inter-dealer trade, where he obtains value W , which is defined below.

Next, we characterize the dealer's policy function following Kalouptsi [2014](#). For tractability, we work under the assumption that : (i) cost shocks $(\epsilon_{d,t}^{\text{buy}}, \epsilon_{d,t}^{\text{sell}}, \epsilon_{d,t}^{\emptyset}) \in \mathbb{R}^3$, are drawn from a double exponential distribution F_0 , with standard deviation σ_0 ; (ii) $\epsilon_{d,t}^1 \in \mathbb{R}$ is drawn from a normal distribution F_1 with

standard deviation σ_1 ; (iii) $\tilde{c}(n) = c_1 |n| + c_2 n^2$ is convex in $|n|$; and (iv) experience transition matrix r can be rewritten as

$$r(e'|e, n, \tilde{e}) = \sum_{e''} r_{\text{d2d}}(e'|e'', \tilde{e}) r_{\text{inv}}(e''|e, n),$$

where r_{d2d} and r_{inv} describe, respectively, the change in experience that can be attributed to inter-dealer trade and to trade with investors. Under these conditions the dealer first decides whether to buy, sell, or avoid trading. Then he decides how many units of the asset to trade, comparing each trading level n to $n+1$ and $n-1$. Denote by $V^{\text{sign}(n)}(\pi, x, e, \epsilon^1)$ the dealer's highest utility conditional on either buying or selling the asset:

$$V^{\text{sign}(n)}(\pi, x, e, \epsilon^1) = \max_{n \in \mathcal{N}(\text{sign}(n))} \left\{ -\tilde{c}(n) - \epsilon_1 |n| - \mathbb{E} \left(\sum_{i=1}^{|n|} p_{it} | \pi, \text{sign}(n) \right) + \mathbb{E} [W(\mathcal{L}_{\text{inv}}(\pi, \vec{p}_{n,t}), x'(n; x), r_{\text{inv}}(n, e))] \right\},$$

where

$$\mathcal{N}(\text{sign}(n)) = \begin{cases} \{1, \dots, N\} & \text{sign}(n) = +1 \\ \{-x, \dots, -1\} & \text{sign}(n) = -1 \end{cases},$$

The probability that dealer d chooses to trade with $n \neq 0$ investors can be written as

$$P(n_{d,t} = n | \pi, x, e) = \int_{\text{lb}(\pi, x, e, n)}^{\text{ub}(\pi, x, e, n)} \frac{\exp\left(\frac{V^{\text{sign}(n)}(\pi, x, e, \epsilon^1) - W(\pi, x, e)}{\sigma_0}\right)}{\exp\left(\frac{V^{\text{sign}(n)}(\pi, x, e, \epsilon^1) - W(\pi, x, e)}{\sigma_0}\right) + \exp\left(\frac{V^{\text{sign}(n)}(\pi, x, e, \epsilon^1) - W(\pi, x, e)}{\sigma_0}\right) + 1} dF_1(\epsilon^1), \quad (7)$$

where $\text{ub}(\pi, x, e, n)$ and $\text{lb}(\pi, x, e, n)$ are optimal policy thresholds defined in Appendix E.

With a standard abuse of notation below we denote

$$V(\pi, x, e) = \mathbb{E}[V(\pi, x, e, \epsilon)].$$

Inter-dealer trade. Consider the situation of a potential buyer with private history (π, x) and experience e , who receives an offer to buy a unit of the asset at price \tilde{q} , from a dealer with experience \tilde{e} . The dealer decides whether to accept the offer by comparing the value from purchasing the asset at price \tilde{q} ,

and from rejecting the offer:

$$\tilde{W}^{\text{buy}}(\pi, x, e; \tilde{q}, \tilde{e}) = \max \left\{ -\tilde{q} + \beta \mathbb{E} \left[V \left(\mathcal{L}_{\text{buy}}(\pi; \tilde{y}, \tilde{q}, \tilde{e}, e), x', r_{d2d}(\tilde{e}, e) \mid e, \tilde{e}, \tilde{q} \right), \beta \mathbb{E} \left[V(\pi, x, r_{d2d}(0, e)) \right] \right] \right\}. \quad (8)$$

If the dealer accepts the offer, he pays price \tilde{q} , his inventory evolves according to $x' = x + 1$, his beliefs evolve following transition 5, and his experience evolves according to transition 2.

Updating rule $\mathcal{L}_{\text{buy}}(\pi; \tilde{y}, \tilde{q}, \tilde{e}, e)$ depends on the signal \tilde{y} that the seller will communicate after trading. When deciding whether to accept offer \tilde{q} , the seller computes the expectation of this signal, conditional on offer \tilde{q} and experience \tilde{e} of his counterparty. Significantly, the offer will depend both on the counterparty's inventory as well as on his beliefs. For this reason, the distribution of signal \tilde{y} conditional on offer \tilde{q} is non-degenerate. If the dealer decides to reject the offer, his experience depreciates and he moves on to the next period, where he will obtain value $\beta \mathbb{E} [V(\pi, x, r_{d2d}(0, e))]$ from trading with investors.

Next, consider the situation of a potential seller with private type (π, x) and experience e , who decides to make an offer to a potential buyer with experience \tilde{e} . The offer $q(\pi, x, e, \tilde{e})$ solves

$$\begin{aligned} \tilde{W}^{\text{sell}}(\pi, x, e; \tilde{e}) = \max_q & \mathbb{P}(\text{accept } q \mid e, \tilde{e}) \beta \mathbb{E} \left[V \left(\mathcal{L}_{\text{sell}}(\pi; \tilde{y}, \tilde{e}, q, e), x', r_{d2d}(\tilde{e}, e) \mid e, \tilde{e}, q \right) \right] \\ & + \mathbb{P}(\text{reject } q \mid e, \tilde{e}) \beta \mathbb{E} \left[V(\pi, x, r_{d2d}(0, e)) \right]. \end{aligned} \quad (9)$$

If the offer is accepted the seller's beliefs evolve according to transition 4, his inventory changes to $x' = x - 1$, and his experience evolves according to transition 2.

Finally, consider the decision of dealer d about the identity of his trading counterparty. The assumption of anonymity allows us to rephrase the potential seller's decision as that of choosing the optimal level of experience of the buyer to whom the offer should be sent:

$$W^{\text{sell}}(\pi, x, e, n; \xi) = \max \left\{ \max_{\tilde{e} \in \{1, \dots, E\}} \left\{ -c^{d2d}(\tilde{e}) + \tilde{W}^{\text{sell}}(\pi, x, e; \tilde{e}) + \xi^{\tilde{e}} \right\}, \beta \mathbb{E} \left[V(\pi, x, r_{d2d}(0, e)) \right] + \xi^0 \right\}. \quad (10)$$

The potential seller decides whether to propose trade to a potential buyer or to move to the next period and obtain value $\beta \mathbb{E} [V(\pi, x, r_{d2d}(0, e))]$. If instead he decides to make an offer to a player of type \tilde{e} , he pays cost $c^{d2d}(\tilde{e}) + \xi^{\tilde{e}}$, and obtains value $\tilde{W}^{\text{sell}}(\pi, x, e, \tilde{e})$, defined in 9. We assume that shocks $\xi \in \mathbb{R}^{E+1}$

are draws from a double exponential distribution F_ξ , with standard deviation σ_ξ . This implies that the probability that a dealer with state (π, x, e) makes an offer to a dealer with experience \tilde{e} satisfies

$$P_e(\tilde{e}|\pi, x, e) = \frac{\exp\left(\frac{-c(\tilde{e}) + \tilde{W}^{\text{sell}}(\pi, x, e, \tilde{e})}{\sigma_\xi}\right)}{\exp\left(\frac{\beta \mathbb{E}[V(\pi, x, r_{\text{d2d}}(0, e))]}{\sigma_\xi}\right) + \sum_{\tilde{e}} \exp\left(\frac{-c(\tilde{e}) + \tilde{W}^{\text{sell}}(\pi, x, e, \tilde{e})}{\sigma_\xi}\right)}. \quad (11)$$

Equation 11 and 10 can be interpreted as an approximation to the discrete choice problem faced by the dealer. Indeed, as cost shock variance σ_ξ converges to zero, $P_e(\tilde{e}|\pi, x, e)$ approaches 1 for level of experience \tilde{e} for which utility $-c(\tilde{e}) + \tilde{W}^{\text{sell}}(\pi, x, e, \tilde{e})$ is largest.

Equilibrium. Dealers' policy functions depend on their current private and public history (π, x, e) , as well as on beliefs about the policies of competitors. Other dealers' beliefs and inventory are unobservable, consistent with the decentralized nature of trade and the opacity of the market. Dealers, therefore, do not observe the valuation for the asset and the policy functions of their peers, but rather have beliefs about these. Beliefs over other dealers' policies and valuations determine dealers behavior in the context of inter-dealer trade. Similarly to [Weintraub et al. 2008](#), we assume that dealers' conjectures about their peers' private state are anchored to their long-run distribution. To allow for learning in the context of inter-dealer trade, however, dealers' conjecture depend on the long run distribution of dealers' private state *conditional* on the unobserved common preference shock θ_t .

Definition. An equilibrium for the market described in the previous section is a distribution $f^*(\pi_d, x_d, e_d|\theta)$ of beliefs π_d , inventory x_d , and experience e_d across dealers conditional on preference shock θ , such that:

1. The distribution of experience in the population does not depend on θ

$$\begin{aligned} f_e^*(\bar{e}|\theta) &= \int_{(e_d=\bar{e})} f^*(\pi_d, x_d, e_d|\theta) d\pi_d dx_d \\ &= f_e^*(\bar{e}). \end{aligned}$$

2. Trading decisions $P_e(\tilde{e}|\pi_d, x_d, e_d)$ and $P_n(n|\pi_d, x_d, e_d)$ are defined in (11) and (7);
3. Offers and replies in the inter-dealer market achieves the optimum in (8) and (9);

4. Conjectures in (11), (7), (8), and (9) are correct given f^* ;
5. Conjectures used for updating, in (5) and (4), are correct given f^* ;
6. Letting $h^*(\theta)$ denote the long-run distribution of θ , and $f^*(\pi_d, x_d, e_d) = \sum_{\theta} f^*(\pi_d, x_d, e_d|\theta) h^*(\theta)$, $f^*(\pi_d, x_d, e_d|\theta)$ is the distribution of dealer's states (π_d, x_d, e_d) within the population implied by transitions (2), (5), (4), (3), and choice probabilities (11) and (7).²¹

5 Empirical Strategy

In this section, we lay out the empirical strategy followed to estimate the model described in Section 4. The main model primitives we wish to recover are dealers' trade costs, $\{c_0, c_1, c_{\text{buy}}, c_{\text{sell}}, c_{\bar{e}}\}$, his inventory costs $\kappa(\cdot)$, as well as the standard deviations of cost shocks. We normalize β to 0.99.

The estimation proceeds in two steps. First, without directly leveraging the model, we recover dealers' experience $e_{d,t}$ and their beliefs $\pi_{d,t}$ about common preference shock θ_t . Next, we estimate dealers' choice probabilities and use them to recover the model primitives through Indirect Inference.

We begin by describing how we define and recover dealers' experience, as well as their beliefs. Next, we show how we recover dealers' search and inventory costs. Finally, in the Appendix, we describe how we recover the process for the unobserved preference shock θ . Results are presented in Section 6.

5.1 Experience

A sizable strand of literature has documented that more experienced firms have a competitive advantage in a variety of industrial settings (most notably, [Benkard 2000, 2004](#)). Experience is usually defined as the discounted sum of past production output. In turn, the marginal cost of production decreases as firms accumulate experience.

In this paper, we rely on the concept of experience to model dealers' incentives in the context of inter-dealer trade. We want to concisely capture the idea that dealers select a trading counterparty based on the information about common shock θ_t that they will be able to extract from him. A dealer's experience offers a tractable way to proxy for the precision of the information that he has been able to gather through

²¹The steady state conditions are spelled out precisely Appendix G.

trade. In this Section we describe how we define experience in the data and, therefore, how we parametrize and recover experience's transition matrix r .

Dealers gain experience both by trading with retail investors and by trading with one another. The information content of inter-dealer trade will depend on how informed the trading counterparty is. For this reason, in contrast to the literature on learning-by-doing, it is not sufficient to keep track the sheer number of trades, but we also need to account for the experience of the trading counterparty.

Concretely, let g_t denote the network defined by inter-dealer trade during month t , with generic entry $g_{d,\tilde{d},t} = \mathbb{I}\{d \text{ and } \tilde{d} \text{ traded in } t\}$ and generic row $g_{d,t}$. Moreover, let $|n_{d,t}|$ denote the total quantity traded by dealer d with private investors in period t . We assume that the experience of dealer d , at the end of month t , for a given asset²² is defined as

$$e_{d,t} = \delta e_{d,t-1} + |n_{d,t}| + \delta \psi_0 g_{d,t} (e_{t-1} - \delta e_{t-2}), \quad (12)$$

with initial values $e_{d,0} = 0$ and $e_{d,-1} = 0$.²³

In Equation 12, parameter δ captures the idea that information becomes less relevant over *time*. Parameter ψ_0 captures the idea that the quality of a piece of information decays every time it is repeated to another agent.

Lemma 1 shows that dealer d 's experience in period t , $e_{d,t}$, can be rewritten as

$$e_{d,t} = \sum_{k \geq 0} \delta^k r_{d,t-k}, \quad (13)$$

²²For tractability we cluster the assets traded in our sample into 15 groups, and estimate the experience process independently across groups.

²³We experiment with numerous formulations for experience and find similar results. Among others, we try: weighting $g_{d,t}$ by the size of trades; using the total volume of trade, rather than $|n_{d,t}|$; using the logarithm of total volume of trade, rather than $|n_{d,t}|$. Finally, definition 12 implicitly assumes that dealers only communicate the information they acquired in the previous period. This assumption can be easily relaxed without drastically changing the results. The advantage of the current set-up is that it minimizes double counting.

where

$$\begin{aligned}
r_{d,t} &= |n_{d,t}| + \delta\psi_0 g_{d,t} |n_{t-1}| + \delta\psi_0 g_{d,t} g_{t-1} |n_{t-2}| + \dots \\
&= |n_{d,t}| + \sum_{k \geq 1} (\delta\psi_0)^k g_{d,t} g_{t-1} \dots |n_{t-k}|.
\end{aligned} \tag{14}$$

This rewriting is useful for interpreting Equation 12. Intuitively, $r_{d,t}$ describes the amount of information obtained by dealer d in period t . The first term in 14, $|n_{d,t}|$, captures the information obtained by dealer d directly by trading with investors. In period t dealer d also obtains information through inter-dealer trade. First, his direct counterparties will share some of the information that they acquired in the previous period by trading with investors. This is captured by the second term in 14, $\delta\psi_0 g_{d,t} |n_{t-1}|$. Dealer d 's counterparties will also share some of the information that they acquired from *their* trading partners (and so on...), as captured by terms $(\delta\psi_0)^2 g_{d,t} g_{t-1} |n_{t-2}|$, $(\delta\psi_0)^3 g_{d,t} g_{t-1} g_{t-2} |n_{t-3}|$, In sum, dealer d 's experience captures in a stylized way the discounted amount of information that that dealer d has obtained up to period t as a result of trade with dealers and investors.

Lemma 1. *Let $r_t = e_t - \delta e_{t-1}$, then r_t satisfies*

$$r_t = n_t + \sum_{k \geq 1} (\delta\psi_0)^k g_t g_{t-1} \dots n_{t-k}.$$

Next, we show that experience is bounded.

Lemma 2. *Let D be the number of dealers in the market, and assume that $|n_t| \leq N$. If $\delta^2\psi_0 < \frac{1}{DN}$, for every g_t and n_t , the experience process $e_t = (e_{1t}, \dots, e_{Dt})$ is bounded.*

Estimation Strategy. Dealer's experience, as defined in (12), depends on two parameters: δ captures the rate of depreciation of information over time, while ψ_0 captures frictions that hinder communication in the context of inter-dealer trade. Due to data limitations, we normalize ψ_0 and focus on the estimation of the depreciation rate δ .

To estimate the parameters, we use a key implication of the model described in Section 4: trading with more experienced counterparties allows the dealers to observe a more informative signal about the

state of the market. For this reason, sellers will be willing to charge a lower price to trade with a more experienced counterparty.

We draw from the literature on learning-by-doing, [Benkard 2000](#) especially, to bring this implication of the model to the data. We consider prices p_i in transactions in the inter-dealer market, and estimate baseline specification

$$\log(p_i) = \alpha_{s_i \times m_i \times a_i} + \alpha_{b_i} + \psi_1 \log(e_{b_i, m_i, a_i}(\delta)) + \psi_2 x_{s_i, m_i} + u_i, \quad (15)$$

where s_i , b_i , a_i and m_i denote, respectively, the seller, buyer, the asset involved in the trade, and the month in which trade happens. The parameter of interest in Equation 15 is δ . We include the coefficient ψ_1 to translate the units of the experience measure into dollars. This parameter measures the discount that a seller is willing to grant to an experienced buyer, and can be thought as a reduced-form measure of a dealers' value for information.²⁴

Identification of the parameters Equation 15 relies on comparisons of inter-dealer prices in trades for specific asset a_i , seller s_i and month m_i . Especially, Equation 15 attributes systematic differences in price across trades executed by seller s_i in month m_i to differences in experience level $e_{b_i, m_i, a_i}(\delta)$ of the buyers involved in the transactions. The fixed effect $\alpha_{s_i \times m_i \times a_i}$ absorbs market-wide shocks to prices, as well as the seller's persistent heterogeneity that might affect prices. We also control for the seller's inventory in x_{s_i, m_i} .

To estimate Equation 15 we exploit the Generalized Method of Moments. The persistency of buyers' experience, together with the inclusion of fixed effect α_{b_i} , raises concerns in the spirit of [Arellano and Bond 1991](#). For this reason we use the lagged values of volume of trade, $n_{b_i, m_i - k, a_i}$, and centrality, $c_{b_i, m_i - k, a_i}$, as instruments.

Endogeneity of u_i could be a potential concern. One could especially worry about persistent (but non-constant) and unobserved heterogeneity that allows buyers both to strengthen their trading activity and to pay lower prices in the inter-dealer market. To control for this scenario, similar to [Li and Schürhoff 2014](#), we also estimate Equation 15 using the monthly aggregate municipal bond mutual fund outflows

²⁴This parameter doesn't have a structural interpretation and we don't use it anywhere else in the estimation. Nevertheless, the sign and magnitude of the estimates of this parameter, reported in Section 6, provide further reduced form evidence about the relevance of experimentation motives for trade.

and inflows, as well as entry and exit of dealers from the market as instruments for buyers' experience, $e_{b_i, m_i, a_i}(\delta)$. Identification of the parameters, in this case, relies on the fact that different dealers have different exposure to shocks captured by the instruments, due to their inventory or clientele.²⁵

5.2 Dealers' Information

Dealers' beliefs $\pi_{d,t} \in \Delta(\Theta)$ about the current value of the unobserved common preference shock θ_t are a key variable to predict their choices. Traditionally, estimating models where learning is explicitly accounted for requires cumbersome computational methods to simulate and integrate out the players' unobservable beliefs. However, thanks to the assumptions made in Section 4 as well as to the granularity of our data set, we can recover dealers' beliefs $\vec{\pi}_t = (\pi_{d,t})_{d=1}^D$ for every period t .

In particular, Proposition 1 shows that the updating rules 4 and 5 can be substantially simplified, as long as after trade the dealers communicate to one another their forecast for the prices. This allows us to recover dealers' beliefs without knowing the equilibrium strategies.

Proposition 1. *Suppose that $y_{d,t} = \pi_{d,t}$, and let $f^*(y|\tilde{e}, \theta)$ denote the distribution of signal \tilde{y} among agents with experience level \tilde{e} , conditional on common shock θ_t . The updating rules 4 and 5 become*

$$\mathcal{L}_{sell}(\pi; \tilde{y}, \tilde{e}) (\theta^k) = \frac{f^*(\tilde{y}|\tilde{e}, \theta^k) \pi(\theta^k)}{\sum_{\theta} f^*(\tilde{y}|\tilde{e}, \theta) \pi(\theta)}, \quad (16)$$

and

$$\mathcal{L}_{buy}(\pi; \tilde{y}, \tilde{e}) (\theta^k) = \frac{f^*(\tilde{y}|\tilde{e}, \theta^k) \pi(\theta^k)}{\sum_{\theta} f^*(\tilde{y}|\tilde{e}, \theta) \pi(\theta)}. \quad (17)$$

We use updating rule 3, together with 16 and 17 to recover dealers' beliefs. This requires running a fixed-point algorithm to recover distribution f^* . Indeed, these updating rules depend on the distribution of dealers' beliefs f^* . In turn, the distribution used for updating affects the evolution of dealers' beliefs.

In brief, our algorithm proceeds in the following steps:

²⁵In light of the inclusion of the fixed effect $\alpha_{s_i \times m_i \times a_i}$, we can ignore the impact of the shocks used as instrument on the market level of prices.

1. Initialize $\left(\bar{\pi}_t^{(0)}\right)_{t \geq 1}$ with $\bar{\pi}_t^{(0)} \equiv \bar{\pi}$, where $\bar{\pi}$ satisfies $\bar{\pi} = h\bar{\pi}$
2. Given a guess for dealers' beliefs $\left(\pi_t^{(m)}\right)_{t \geq 1}$, compute the distribution of dealers' beliefs after inter-dealer trade
 - (a) First, given beliefs $\left(\pi_t^{(m)}\right)_{t \geq 1}$, compute the distribution of dealers' beliefs after trade with investors, conditional on experience and the unobserved state θ . In particular, for every d and t , compute $\hat{\pi}_{d,t}^{(m)} = \mathcal{L}_{inv} \left(h' \pi_{d,t}^{(m)}; \vec{p}_{n,t} \right)$, and estimate $\hat{f}^{(m)} \left(\hat{\pi}_{d,t}^{(m)} | \theta^k, e_{d,t} \right)$.
 - (b) Next, update dealers' beliefs based on the interaction on the inter-dealer market. Dealer d , with beliefs $\hat{\pi}_{d,t}^{(m)}$, after buying an asset from dealer \tilde{d} updates according to

$$\hat{\pi}_{d,t}^{(m)} = \mathcal{L}_{buy} \left(\hat{\pi}_{d,t}^{(m)}; y_{\tilde{d},t}, e_{\tilde{d},t} \right).$$

For sellers instead

$$\hat{\pi}_{d,t}^{(m)} = \mathcal{L}_{sell} \left(\hat{\pi}_{d,t}^{(m)}; y_{\tilde{d},t}, e_{\tilde{d},t} \right).$$

- (c) set $\pi_{d,t}^{(m+1)} = h' \hat{\pi}_{d,t}^{(m)}$.
3. If $\int \left| \hat{f}_0^{(m+1)} \left(\hat{\pi}_{d,t}^{(m)} | \theta_t, e_{d,t} \right) - \hat{f}_0^{(m-1)} \left(\hat{\pi}_{d,t}^{(m)} | \theta_t, e_{d,t} \right) \right| \hat{f}_0^{(m-1)} \left(\hat{\pi}_{d,t}^{(m)} | \theta_t, e_{d,t} \right) d\pi < \epsilon$, set

$$\left(\pi_t^*\right)_{t \geq 1} = \left(\pi_t^{(m)}\right)_{t \geq 1}.$$

Otherwise repeat steps 2 and 3.²⁶

5.3 Dealers' Costs

We next turn to the model's primitives: inventory cost $\kappa = \{\kappa_0, \kappa_1\}$, costs to trade with investors $\{c_{buy}, c_{sell}, c_1, c_2\}$, costs to trade with other dealers $\{c_{\tilde{e}}\}_{\tilde{e}=1}^E$ and the standard deviations of cost shocks

²⁶We assume that our data comes from one steady state, so that the distribution $f^*(\pi_{d,t} | \theta, e_{d,t})$ is fixed over time. Furthermore, the assumption of anonymity requires that dealers with the same experience are seen as equivalent from their peers, which implies that the update in (16) and (17) does not depend on d . Finally independence ensures that rules (16) and (17) do not depend on the dealer's own private state.

$\{\sigma_\xi, \sigma_0, \sigma_1\}$. To obtain the parameters of interest, we use dealers' optimal trade choice probabilities defined in Equation 7 and 11, as well as prices on the inter-dealer market. Both of these are a function of the dealers' value functions, which in turn depend on the parameters.

We estimate the parameters via Indirect Inference, following [Gourieroux et al. 1993](#). As auxiliary models we employ an ordered Probit and multinomial Logit for, respectively, the trading decision with investors and trading decision with other dealers.

Concretely, we use the observed data to obtain the parameter estimates $\hat{\beta} = \left(\beta_{\text{aux}}, (\beta_{\text{aux}}^{\tilde{e}})_{\tilde{e}=1}^E \right)$ and $\hat{\alpha} = (\alpha_{\text{aux}}^n)_{n=1}^N$ that maximize the likelihood associated to the auxiliary model

$$\begin{aligned} \mathcal{L}(\mathbb{I}; \alpha, \beta, z) &= \sum_d \sum_t \sum_n \mathbb{I}_{d,t,n} \log \left(\Phi \left(z'_{d,t,n} \beta_{\text{aux}} - \alpha_{\text{aux}}^n \right) - \Phi \left(z'_{d,t,n} \beta_{\text{aux}} - \alpha_{\text{aux}}^{n-1} \right) \right) \\ &\quad + \sum_d \sum_t \sum_n \mathbb{I}_{d,t,\tilde{e}} \log \left(\frac{\exp \left(z'_{d,t,n} \beta_{\text{aux}}^{\tilde{e}} \right)}{\sum_{\tilde{e}} \exp \left(z'_{d,t,n} \beta_{\text{aux}}^{\tilde{e}} \right)} \right), \end{aligned}$$

where $\mathbb{I}_{d,t,n}$ is an indicator equal to 1 if dealer d chooses n in period t ; $\mathbb{I}_{d,t,\tilde{e}}$ is an indicator equal to 1 if dealer d sells to a dealer with experience \tilde{e} in period t , and $z_{d,t,n}$ is the state variable of dealer d in period t , $z_{d,t} = (\pi_{d,t}, x_{d,t}, e_{d,t})$.

Next, at every guess of primitive parameter value $\tau = \{c_{\text{buy}}, c_{\text{sell}}, c_1, c_2, c_{\tilde{e}}, \kappa_0, \kappa_1, \sigma_0, \sigma_1, \sigma_\xi\}$, we use a nested fixed point algorithm to solve for the dealer's value functions (V, W) and generate M simulated data sets $\left\{ \mathbb{I}_{d,t,\tilde{e}}^{(m)}, \mathbb{I}_{d,t,\tilde{e}}^{(m)} \right\}_{m=1}^M$. Finally, we use the simulated dataset to retrieve the parameters $(\beta^{(m)}(\tau), \alpha^{(m)}(\tau))$ that maximize the auxiliary likelihood $\mathcal{L}(\tilde{\mathbb{I}}; \alpha, \beta, z)$. The estimated primitive parameter $\hat{\tau}$ minimizes

$$\mathcal{L}(\mathbb{I}; \hat{\alpha}, \hat{\beta}, z) - \mathcal{L}(\mathbb{I}; \bar{\alpha}(\tau), \bar{\beta}(\tau), z),$$

where $\bar{\beta}(\tau) = \frac{1}{M} \sum_{m=1}^M \beta^{(m)}(\tau)$, and $\bar{\alpha} = \frac{1}{M} \sum_{m=1}^M \alpha^{(m)}(\tau)$. In Appendix F we outline the specific steps we follow in the estimation algorithm.

Identification. Estimation of the parameters in τ relies on the dynamic panel nature of the data. Observing dealers' decision over time allows us to keep track of how their behavior change depending on their type (π, x, e) . These changes in behavior identify the parameters.

Conceptually, identification of standard deviations $\{\sigma_0, \sigma_1\}$ —associated to the cost shocks in the context of trade with investors— is driven by differences in dealers trading decisions across different beliefs π , conditional on observed trading prices. As standard deviation σ_0 —which affects the decision on whether to buy or sell the asset— increases, dealers will choose to either sell or purchase the asset with the same probability for any belief π . As standard deviation σ_1 increases, the dealer will randomize between trading the highest and the lowest possible amount of units of the asset. Finally, sheer trading costs $\{c_{\text{buy}}, c_{\text{sell}}, c_1, c_2\}$ are pinned down by the overall level of trade.

Identification of trade costs in inter-dealer trade $\{c_{\bar{e}}\}_{\bar{e}=1}^E$ depends in a similar fashion on dealers’ decisions in the context of inter-dealer trade. Importantly, we rely on data on prices for inter-dealer trades to anchor the unit of utility from inter-dealer trade. This allows us to identify standard deviation σ_{ξ} .

Finally, prices in inter-dealer trades as a function of the seller’s inventory x help us to identify inventory costs κ . If the inventory cost is high the trading price will sharply fall as dealer’s inventory increases, holding everything else fixed.

6 Results

In this section we present the results from our empirical analysis. Throughout the estimation, we group assets into 15 different classes and consider each class as a separate market. The classes are determined, through a clustering algorithm, to maximize the correlation over time of the average price within each class.²⁷ Appendix C describes how we recover Θ , sequence $(\theta_t)_{t \geq 1}$, and transition matrix h . For each class, common shock θ_t can take at most three values.

6.1 First stage

We now show the results from the first stage of the estimation described in Sections 5.1 and 5.2.

We estimate Equation 12 separately for each class of assets. Table 3 shows the average estimated parameters, across classes of assets, for the experience process. The top panel reports the results from our baseline estimation, while the bottom panel reports those from the instrumented version. Table 9 in the Appendix presents the results separately for each class.

²⁷For details, see Appendix D

For each class, the experience discount, as measured by ψ_1 , is negative and significant at the 1% level. Dealers, therefore, are willing to pay a premium to trade with more experienced counterparties. The average trading price falls by 0.17 percentage points when the buyer belongs to the 75th percentile of the experience distribution, compared to when it belongs to the 25th percentile. This amounts to approximately 10% of the average intermediation spread.²⁸ Consistent with the volatile nature of the market, information appears to be short-lived. The value of δ is around 0.55 in both specifications. This implies that only 2% of the accumulated experience lives through six months.

To validate these results, in Figure 4 we compare the estimates of ψ_1 for each class of assets with the variability of prices over time for the same class of assets. Intuitively, for assets for which price is less uncertain, experience discount $|\psi_1|$ should be smaller. On the vertical axis of Figure 4 we plot the estimate for ψ_1 . On the horizontal axis we report the R^2 from the regression of the current average price on market indexes. Assets for which the R^2 is larger are easier to forecast based on information publicly known. We find that for classes of assets associated with larger values of R^2 , the experience discount is smaller. The (weighted) correlation²⁹ between the two values is 26%.

Table 3: Experience process

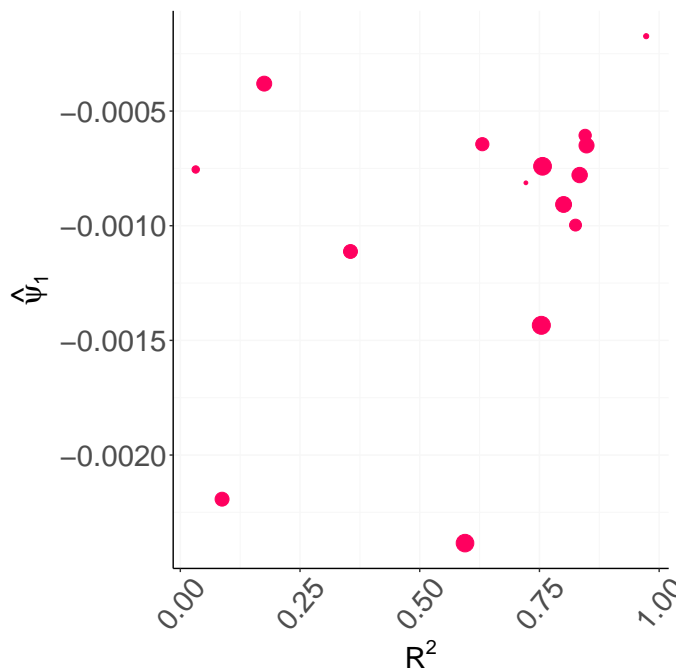
	Persistence of Information δ	Experience Premium ψ_1	Learning Rate $1 - 2^{\psi_1}$
I	0.582	-0.0017	0.118%
II	0.53	-0.0013	0.09%

Notes: The table above summarizes the estimates of the Experience process defined in Equation 12. We cluster the assets in our sample into 15 groups and estimate the experience process independently across groups. In the table above we report the average parameter across classes. For the top row we use past trading activity as an instrument. For the bottom row we use instruments defined in Section 5.1.

²⁸The learning rate $1 - 2^{\psi_1}$ captures the percentage reduction in price associated with a doubling of experience.

²⁹We weight the correlation using the total value of the trades for each group of assets.

Figure 4: Comparison of risk and ψ_1 estimates across classes of assets.



Notes: the above figure compares experience discount ψ_1 and price uncertainty across assets groups. On the vertical axis we plot the estimate of experience discount ψ_1 . To proxy for the price uncertainty of different groups of assets, on the horizontal axis we plot the R^2 of a regression of monthly average price within a class of assets on public indexes about on the performance of the market for municipal bonds.

6.2 Dealers' Costs

Table 4 reports the average baseline estimates for the model primitives across classes of inventory. Namely, inventory costs $\{\kappa_0, \kappa_1\}$, costs to trade with investors $\{c_{\text{buy}}, c_{\text{sell}}, c_1, c_2\}$ and with other dealers $\{c_{\bar{e}}\}_{\bar{e}=1}^E$, and the standard deviations of cost shocks $\{\sigma_{\xi}, \sigma_0, \sigma_1\}$.

Trade costs are large, with the average dealer spending on average \$3,000 per class of assets each month to find investors. The total search cost is on average \$50,000 per month and dealer. The standard deviation of the preference shocks, σ_1 , equals roughly 16% of the trading price, suggesting that that preference shocks ϵ^1 do not account for a disproportionately large part of the decision on how many investors to trade with. Consistent with the industry narrative, dealers receive higher fees when they sell assets to investors, obtaining net fees of around \$1,300 per class of asset traded. Search costs, instead, dominate when it comes to buying assets, as dealers pay net fixed cost of around \$1,000 if they decide to

buy the asset.

If we interpret the inventory cost in terms of leverage, the estimates imply that 15% of the inventory is collateralized, as long as the dealers can borrow at the deposit funds rates. The difference in cost of inventory across assets is explained by the rating of the assets traded. In particular, doubling the number of assets with a B-rating doubles the cost of inventory for a class of assets.³⁰ This is consistent with, as an example, dealers targeting a certain value-at-risk level when managing inventory.

Table 4: Baseline cost estimates

Trade with Investors		Fees		Interdealer Trade			Inventory Costs		Variance		
c_1	c_2	c_{buy}	c_{sell}	$\tilde{c}_{\tilde{e}_1}$	$\tilde{c}_{\tilde{e}_2}$	$\tilde{c}_{\tilde{e}_3}$	κ_0	κ_1	σ_ξ	σ_1	σ_0
0.018	0.012	0.023	-0.020	-0.040	-0.019	-0.020	0.003	0	0.11	0.19	0.10

Notes: The table above summarizes the estimates of the trading costs that dealer faces. We cluster the assets in our sample into 15 groups and estimate these costs independently across groups. In the table above we report the average parameter across classes.

7 Value and Precision of Information

Next, we explicitly characterize the dealers’ incentives to experiment. We begin by comparing the informativeness of trades with investors and inter-dealer trades. Next, we show to what extent experimentation helps dealers refine their estimate about the state of fundamentals. Moreover, we study the origin of dealer’s information. Finally, we characterize the dealers’ value of information. For all these exercises we use the biggest group of assets.

7.1 Precision of Information

To compare the informativeness of different types of signals, we study the precision of the forecast for the trading price $\mathbb{E}(p_i|\pi, \mathcal{I}) = \sum_{\theta \in \Theta} \pi(\theta|\mathcal{I}) \mathbb{E}(p_i|\theta)$ of a dealer with belief π , who receives information \mathcal{I} . In

³⁰Rating explains 40% of the variation in inventory cost across classes.

particular we average (and square) the value of $[\mathbb{E}(p_i|\theta_t) - \mathbb{E}(p_i|\pi, \mathcal{I})]^2$ across different realizations of θ_t ,

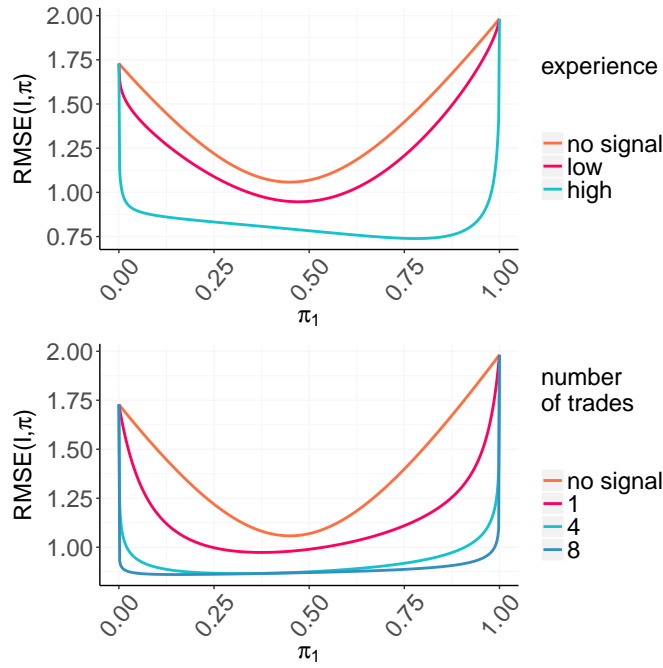
$$RMSE(\pi, \mathcal{I}) = \sqrt{\mathbb{E}\left([\mathbb{E}(p_i|\theta_t) - \mathbb{E}(p_i|\pi, \mathcal{I})]^2\right)}. \quad (18)$$

Intuitively, $\mathbb{E}\left([\mathbb{E}(p_i|\theta_t) - \mathbb{E}(p_i|\pi, \mathcal{I})]^2\right)$ captures the average difference in the mean squared error of the best prediction for trading price p_i of a dealer with belief $\pi(\theta|\mathcal{I})$, compared to a dealer who knew the realization of θ_t .

Figure 5 plots $RMSE(\pi, \mathcal{I})$ for different information sets \mathcal{I} and dealers' prior beliefs π . In all cases $|\Theta| = 3$, so that $\pi \in \Delta^2$. We set the probability for the middle state to zero, and plot the probability of the low state, π_1 , on the horizontal axes. Different lines correspond to different signals (i.e., different information sets \mathcal{I}). In the lower panel, we plot the informativeness of trade with investors for different numbers of trades. The upper panel depicts the informativeness of the signal obtained by trading with another dealer for different levels of experience. We also include the root mean squared error of the estimate of θ_t absent any additional information (orange line). As one could have guessed, the signal is more informative if the dealer trades more or if he trades with a more experienced dealer. Furthermore a dealer is more easily convinced if his prior beliefs are more dispersed. In particular, the root mean squared error falls at most by 40% if the dealer decides to trade with an experienced dealer (blue line), and at most by 20% if the dealer trades with an inexperienced counterparty. Trading with a single investor is as informative as trading with the average inexperienced trader, as the RMSE falls at most by 15% in the latter case. Trading with an experienced dealer instead is as informative as trading with 5 different investors.

Next, we look at the uncertainty in dealers' estimate of trading prices taking into account their equilibrium behavior. In Table 5 we compute the average RMSE across players, at the observed equilibrium, for different types of dealers. The first column reports the upper bound for the RMSE when the agents only observe public signal y_t^P . The last three columns show the RMSE attained in equilibrium for dealers with different experience levels. Experimentation allows dealers to improve the precision of their estimate on average by 25%. Experienced dealers have better information than the rest of the market, as they are able to improve the precision of their prediction by 33% compared to when they did not experiment. The improvement in precision is lower for inexperienced dealers, who improve the precision of their estimate

Figure 5: Informativeness of different signals



Notes: the above figure plots the root mean square error $RMSE(\pi, \mathcal{I})$ for different signals and dealers' prior beliefs π . In all cases $|\Theta| = 3$, and we set the probability for the middle state to zero. The probability of the low state π_1 , is shown on the horizontal axes. Different lines correspond to different information sets \mathcal{I} . In the lower panel, we plot $RMSE(\pi, \mathcal{I})$ after dealers traded with investors. The upper panel depicts the value of $RMSE(\pi, \mathcal{I})$ after trading with another dealer.

by 23%.

Table 5: Precision of information

	Uninformed Players	Market Average	Inexperienced Players	Experienced Players
RMSE	1.024	0.759	0.782	0.691
Percentage	100	74.15	76.43	67.49

Notes: We compute the measure defined in Equation 18 for dealers along the equilibrium path. The table above reports the average across beliefs π for different classes of dealers. The first column reports the measure for players with access only to public information. The second column reports the average across all players, and the last two columns distinguish among experienced and inexperienced players.

Next we study how information percolates in the market. To this end, we use the estimated policy functions to simulate the game under the assumption that dealers only update based on information from inter-dealer trade with a specific type of dealer or based on trade with investors. Table 6 reports the percentage of the increase in precision that can be attributed to different sources of information. Experienced dealers learn mainly from other dealers, as only 19% of their information derives from trade with investors. Inexperienced dealers rely more heavily on trade with investors, which accounts for one-third of their information. For both experienced and inexperienced players, trade with inexperienced dealers accounts for the largest share of information acquired the context on inter-dealer trade. The difference is sharper for inexperienced dealers: only 22% of information that inexperienced dealers gather derives from trade with experienced dealers.

7.2 Value of Information

To quantify dealers' incentives to experiment, we characterize the value of information for the dealers active in the market for municipal bonds. Intuitively, in our estimation the dealers' value for information is identified using prices in the inter-dealer market: the discount that a dealer is willing to offer to trade with a more experienced counterparty allows us to measure the value he assigns to a more informative signal.

Table 6: Origin of information

	Trade with Investors	Inter-dealer Trade		
		Low Experience	Middle Experience	High Experience
Experienced Players	0.19	0.288	0.262	0.254
Inexperienced Players	0.304	0.30	0.278	0.223

Notes: The table above decomposes improvement in dealers' information described in Table 5. The first column shows what percentage of dealers' information derives from trade with investors. The last three columns show what percentage of dealers' information derives from trade with dealers with different experience levels.

For a dealer with prior beliefs π , inventory x and experience level e , the value of a signal $y|\theta \sim f_y$ is

$$VI(\pi, x, e, f_y) = \mathbb{E}(V(\mathcal{L}(y, \pi), x, e)) - V(\pi, x, e), \quad (19)$$

where the first expectation is taken with respect to realizations of y , and $\mathcal{L}(y, \pi)$ denotes the updated belief based on observing the realization of signal y :

$$\begin{aligned} \pi'(\theta^k)(y) &= \frac{f(y|\theta^k) \pi(\theta^k)}{\sum_{\theta \in \Theta} f(y|\theta) \pi(\theta)} \\ &= \mathcal{L}(y, \pi). \end{aligned}$$

The value of VI can be interpreted as the highest price that a dealer with beliefs π , inventory x and experience level e is willing to pay to purchase signal y about θ . The upper panel of Figure 6 shows the value of information for different prior beliefs π and different distributions f_y . For simplicity, we focus on normal signals, $y|\theta \sim N(\theta, \sigma_I^2)$, and normalize the precision of signal y , $\frac{1}{\sigma_I}$, based on the standard deviation of the public signal about θ , $\frac{1}{\sigma_I} = \frac{\gamma}{\sigma_P}$. Finally, to fix magnitudes, we normalize value of information using the average intermediation spread. In sum, the plot should be interpreted as the share of the intermediation spread that a dealer is willing to give up to buy a signal about θ which is γ times more informative than the public signal y_t^P .

The lower panel of Figure 6 shows the marginal value of information

$$MVI(\pi, x, e, f_y) = \frac{VI(\pi, x, e, f_{y_h}) - VI(\pi, x, e, f_y)}{h}, \quad (20)$$

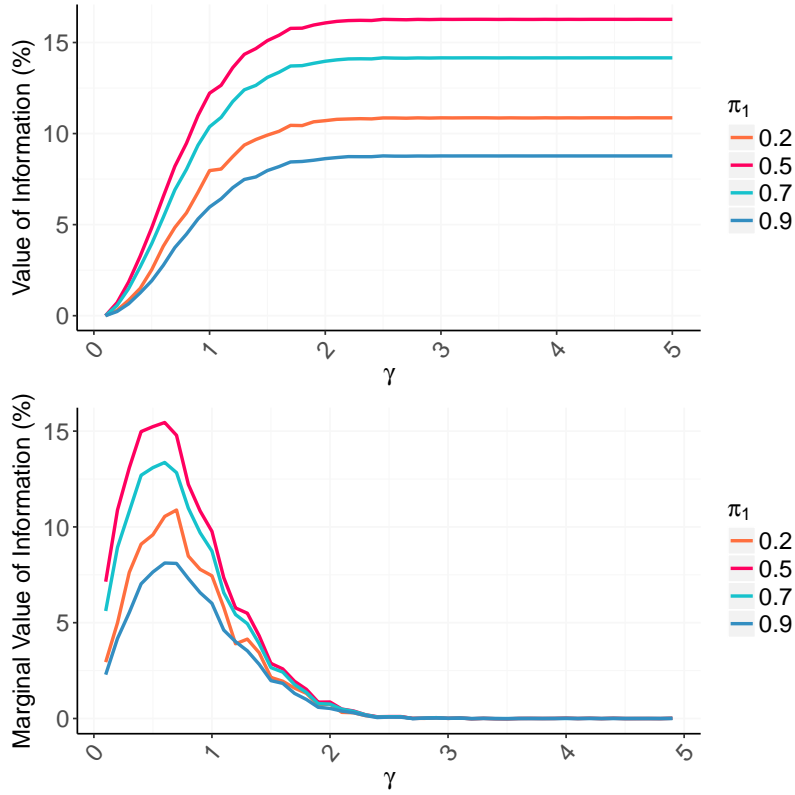
where $f_{y_h} = N\left(\theta, \left(\frac{\sigma_P}{\gamma+h}\right)^2\right)$ is the distribution of a slightly more precise signal than $f_y = N\left(\theta, \left(\frac{\sigma_P}{\gamma}\right)^2\right)$.

Both value and marginal value of information are computed at the average level of inventory \bar{x} and normalized using the average intermediation spread.

The estimated value of information is positive and substantial. Dealers benefit from having precise information about the market fundamental θ . As an example, the average dealer is willing pay up to 15% of its intermediation spread to acquire a signal about θ twice as informative as the public signal.

The marginal value of information is initially zero as found in Radner and Stiglitz 1984 and rigorously formalized in Chade and Schlee 2002. The marginal value is hump shaped. This is consistent with what Keppo et al. 2008 find in a Gaussian setting. The shape of the marginal value can have far-reaching implications for the market. For example, it creates a scope for a dealer's specialization that is consistent with the tendency of dealers to specialize in a specific class of assets.

Figure 6: Value and marginal value of information



Notes: The top panel of the above figure plots the share of the average intermediation spread that a dealer is willing to give up to buy a noisy signal of common shock θ with distribution $y|\theta \sim N\left(\theta, \frac{\gamma}{\sigma_P}\right)$, where σ_P is the variance of the public signal y_t^P . Different lines corresponds to different prior beliefs π . In particular, in all cases $|\Theta| = 3$, and we set the probability for the middle state to zero. Each line correspond to a different probability of the low state π_1 . Instead, the bottom panel of the figure plots the difference in the dealer's valuation for a signal $y|\theta \sim N\left(\theta, \frac{\gamma}{\sigma_P}\right)$ and a slightly less informative signal $N\left(\theta, \frac{\gamma-h}{\sigma_P}\right)$ normalized by h , for small values of h .

8 Implications for Market Transparency

Traditionally, assets in decentralized markets are traded in an opaque environment, with limited or no public information about market activity. In the last decade, however, access to trade information has improved in many decentralized markets, mostly due to direct intervention of the policy maker. As an example, in 1995 the MSRB took the first steps of the plan that led, in 2005, to the 15-minute reporting discussed in Section 3. Shortly after, in 2002, a similar provision was imposed by The Financial Industry Regulatory Authority (FINRA) in the market for U.S. corporate bonds. In 2011 Agency-Backed Securities and Asset-Backed Securities followed. Finally, in 2014 FINRA began disseminating 144A transactions.

The push toward greater transparency in decentralized markets is still ongoing, both in the US and abroad. As an example, in July FINRA began requiring its member firms to report U.S. Treasury securities transactions, even though those prices are currently not disseminated to the public. In Europe the legislative package comprising the revised Markets in Financial Instruments Directive and a new Regulation (“MiFID II”), passed into law in 2014, is about to institute a post-trade transparency regime which will affect a broad range of instruments.

The stated objective behind these policies is to increase the assets’ liquidity by improving investor participation and trade activity.³¹ An asset is considered more liquid “if it is more certainly realizable at short notice without loss.” Therefore, liquidity is valuable per se, as long as investors value immediacy. Moreover, a liquid secondary market is a crucial condition to lower the cost of raising capital. As an example, Wang et al. 2008 estimate that the municipal bond issuers pay 13 billion a year to compensate investors for the risks implied by the illiquidity of the market. Increasing liquidity in this market, therefore, would translate to huge savings for local governments and municipalities.

The argument for the effectiveness of the policy goes as follows: dealers have an informational advantage vis-a-vis investors. This advantage is leveraged to “buy low and sell high.” This lowers liquidity directly, since it lowers the price that an investor can obtain by selling his assets before maturity. Moreover, dealers’ market power lowers liquidity indirectly, since higher prices on the buy side depress buyers’ participation. Improving access to public information, therefore, should reduce dealers’ market power and increase market liquidity.

³¹Testimony of Chairman Arthur Levitt Before the House Subcommittee on Finance and Hazardous Materials, Committee on Commerce, Concerning Transparency in the United States Debt Market and Mutual Fund Fees and Expenses.

This argument, however, ignores a key driving force of market liquidity: the dealers’ incentives to participate to trade. In particular, if information acquisition is a key determinant of dealers’ trading decisions, improving access to public information might weaken their incentives to trade and dampen or overturn the positive effects of investors’ participation.

We use the estimated model to qualify this statement. In particular, we quantify the effect of an increase in market transparency of dealers’ incentives to trade. To approximate a transparent market, we simulate the model assuming that the terms of trade of all transactions become public at the end of each period. Once public, information about trade activity can be observed, free of charge, by everyone.

On average dealers are willing to buy 4% fewer assets from investors, once market transparency is improved. In particular, Table 7 shows that on average (across assets) dealers’ purchase increase by 4% when the market value for the asset increase. This change is offset by the change in trading behavior for other realizations of the asset.

Table 7: Effect of market transparency

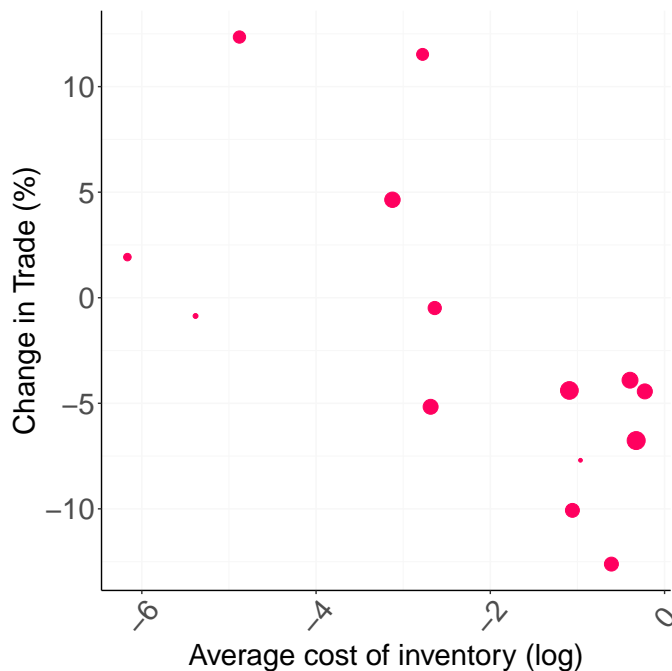
State (θ_t)	Low	Medium	High
Purchases from investors (Overall Change)	4.97%	-4.72%	-8.68%
(Billion \$)	8.00	-5.1	-14.95

Notes: the table above summarizes the change in volume of dealers’ assets purchases that results from an increase in market transparency. In particular we report the average change across different classes of assets, for different values of common preference shock θ_t .

Two effects are at play. First, transparency weakens the incentives to experiment: when information trading activity is made public, uncertainty about common shock θ_t is drastically reduced. Therefore, the value of additional information conveyed by trade becomes irrelevant. This makes each trade less valuable for the dealers and implies that, conditional on private history (π, x, e) , dealers are willing to trade more sporadically. Second, improving public information reduces uncertainty about the realization of the preference shock θ_t . Lower uncertainty implies that dealers are more willing to trade larger quantities of the asset, partially offsetting the first effect.

The balance between these two effects varies substantially across assets. As shown in Figure 7, the

Figure 7: Total change in volume of trade as a function of cost of inventory



Notes: The figure above compares the total change in volume associated to an increase in market transparency with the estimated cost of inventory κ_0 across different classes of assets. For each class of assets, the size of the associated point is proportional to the observed total value of trade for the assets included in the class.

average change within classes of assets ranges from -10% to $+10\%$. This suggests that the success of this policy will hinge on the underlying features of the assets traded.

Estimated cost of inventory $\hat{\kappa}_0$ is the strongest predictor for the effect of market transparency, and accounts for more than 50% of the differences in market outcome across classes of assets. This result is intuitive: as the limits to expand inventory become stronger, the dealer will find it more difficult to adjust his trading decisions to exploit fluctuations in common shock θ_t . This contains the first effect described above, since the dealer is in a worse position to leverage information acquired thanks to market transparency, and it implies that the decline in volume of trade is sharper.

9 Conclusion

In this paper, we shed new light on the role of experimentation in decentralized opaque markets. These markets are common in wholesale trade markets and markets for investment goods. We argue that in

these markets trade can be a source of valuable information about the market fundamentals. Obtaining this information, therefore, becomes an additional motive for trade.

To characterize incentives to experiment, we use a detailed dataset of transactions on the secondary market of municipal bonds, which provides a comprehensive insight into a decentralized financial market. We first use the dataset to provide reduced form evidence suggesting that incentives to experiment are a first-order motive for trade in the market. To rationalize these facts we build a dynamic model of trade in decentralized markets where agents are uncertain about the underlying value of the asset traded. Using the data we estimate the model and demonstrate that experimentation explains up to 10% of the volume of trade in this market. Finally we show that accounting for experimentation is important for a number of policies, such as increasing market transparency as well as imposing limits on inventory holding.

References

- Admati, Anat R. and Paul Pfleiderer**, “A theory of intraday patterns: Volume and price variability,” *The Review of Financial Studies*, 1988, 1 (1), 3–40.
- Aghion, Philippe, Maria Paz Espinosa, and Bruno Jullien**, “Dynamic duopoly with learning through market experimentation,” *Economic Theory*, 1993, 3 (3), 517–539.
- Aguirregabiria, Victor and Pedro Mira**, “Sequential Estimation of Dynamic Discrete Games,” *Econometrica*, 2007, 75 (1), 1–53.
- Arellano, Manuel and Stephen Bond**, “Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations,” *The Review of Economic Studies*, 1991, 58 (2), 277–297.
- Asquith, Paul, Thom Covert, and Parag Pathak**, “The effects of mandatory transparency in financial market design: Evidence from the corporate bond market,” *National Bureau of Economic Research*, 2013.
- Bajari, Patrick, C. Lanier Benkard, and Jonathan Levin**, “Estimating Dynamic Models of Imperfect Competition,” *Econometrica*, 2007, 75 (5), 1331–1370.
- Benkard, C. Lanier**, “Learning and Forgetting: The Dynamics of Aircraft Production.,” *American Economic Review*, 2000, 90 (4), 1034–1054.

- , “A dynamic analysis of the market for wide-bodied commercial aircraft,” *The Review of Economic Studies*, 2004, 7 (31), 581–611.
- Bloomfield, Robert and Maureen O’Hara**, “Market transparency: Who wins and who loses?,” *The Review of Financial Studies*, 1999, 12 (1), 5–35.
- and — , “Can transparent markets survive?,” *Journal of Financial Economics*, 2000, 55 (3), 425–459.
- Blouin, Max R. and Roberto Serrano**, “A decentralized market with common values uncertainty: Non-steady states,” *The Review of Economic Studies*, 2001, 68 (2), 323–346.
- Chade, Hector and Edward Schlee**, “Another look at the Radner–Stiglitz nonconcavity in the value of information,” *Journal of Economic Theory*, 2002, 107 (2), 421–452.
- Chandrasekhar, Arun G., Horacio Larreguy, and Juan Pablo Xandri**, “Testing models of social learning on networks: Evidence from a framed field experiment,” *Work. Pap., Mass. Inst. Technol., Cambridge, MA*, 2012.
- Dickstein, Michael J. and Eduardo Morales**, “What do exporters know?,” *National Bureau of Economic Research*, 2015.
- Duffie, Darrell and Gustavo Manso**, “Information percolation in large markets,” *The American economic review*, 2007, 97 (2), 203–209.
- , **Nicolae Gârleanu, and Lasse Heje Pedersen**, “Over-the-Counter Markets,” *Econometrica*, 2005, 73 (6), 1815–1847.
- , — , and — , “Valuation in over-the-counter markets,” *The Review of Financial Studies*, 2007, 20 (6), 1865–1900.
- Ellison, Glenn and Drew Fudenberg**, “Rules of thumb for social learning,” *Journal of Political Economy*, 1993, 101 (4), 612–643.
- and — , “Word-of-mouth communication and social learning,” *The Quarterly Journal of Economics*, 1995, 110 (1), 93–125.
- Ericson, Richard and Ariel Pakes**, “Markov-Perfect Industry Dynamics: A Framework for Empirical Work,” *The Review of Economic Studies*, 1995, 62 (1), 53–82.
- Farboodi, Maryam, Gregor Jarosch, and Robert Shimer**, “Meeting technologies in decentralized asset markets,” *Working Paper*, 2016.

- Gavazza, Alessandro**, “Leasing and secondary markets: Theory and evidence from commercial aircraft,” *Journal of Political Economy*, 2011, 119 (2), 325–377.
- , “The Role of Trading Frictions in Real Asset Markets,” *American Economic Review*, 2011, 101 (4), 1106–43.
- Golosov, Mikhail, Guido Lorenzoni, and Aleh Tsyvinski**, “Decentralized trading with private information,” *Econometrica*, 2014, 82 (3), 1055–1091.
- Gourieroux, Christian, Alain Monfort, and Eric Renault**, “Indirect inference,” *Journal of Applied Econometrics*, 1993, 8 (S1).
- Green, Richard C., Dan Li, and Norman Schürhoff**, “Price discovery in illiquid markets: Do financial asset prices rise faster than they fall?,” *The Journal of Finance*, 2010, 65 (5), 1669–1702.
- Grossman, Sanford J., Richard E. Kihlstrom, and Leonard J. Mirman**, “A Bayesian approach to the production of information and learning by doing,” *The Review of Economic Studies*, 1977, pp. 533–547.
- Harris, Lawrence E and Michael S Piowar**, “Secondary trading costs in the municipal bond market,” *The Journal of Finance*, 2006, 61 (3), 1361–1397.
- Hopenhayn, Hugo A.**, “Entry, Exit, and Firm Dynamics in Long Run Equilibrium,” *Econometrica*, 1992, 60 (5), 1127–1150.
- Hörner, Johannes and Andrzej Skrzypacz**, “Learning, Experimentation and Information Design,” 2016.
- Hugonnier, Julien, Benjamin Lester, and Pierre-Olivier Weill**, “Heterogeneity in decentralized asset markets,” *National Bureau of Economic Research*, 2014.
- Jovanovic, Boyan**, “Learning By Doing and the Choice of Technology,” *Econometrica*, 1996, 64 (6), 1299–1310.
- Kalouptsi, Myrto**, “Detection and Impact of Industrial Subsidies: The Case of World Shipbuilding,” *American Economic Review*, 2014, 104 (2), 564–608.
- Keppo, Jussi, Giuseppe Moscarini, and Lones Smith**, “The demand for information: More heat than light,” *Journal of Economic Theory*, 2008, 138 (1), 21–50.
- Kihlstrom, Richard, L. Mirman, and Andrew Postlewaite**, “Experimental Consumption and the ‘Rothschild Effect’,” *Bayesian Models of Economic Theory*, 1984.
- Kyle, Albert S.**, “Continuous auctions and insider trading,” *Econometrica*, 1985, pp. 1315–1335.

- , “Informed speculation with imperfect competition,” *The Review of Economic Studies*, 1989, 56 (3), 317–355.
- Leach, J. Chris and Ananth N. Madhavan**, “Price experimentation and security market structure,” *The Review of Financial Studies*, 1993, 6 (2), 375–404.
- Lerman, Kristina, Rumi Ghosh, and Jeon Hyung Kang**, “Centrality metric for dynamic networks,” *Proceedings of the Eighth Workshop on Mining and Learning with Graphs*, 2010, (70–77).
- Li, Dan and Norman Schürhoff**, “Dealer networks,” 2014.
- Miao, Jianjun**, “A search model of centralized and decentralized trade,” *Review of Economic Dynamics*, 2006, 9 (1), 68–92.
- Mirman, Leonard J., Larry Samuelson, and Amparo Urbano**, “Monopoly experimentation,” *International Economic Review*, 1993, pp. 549–563.
- Pagano, Marco**, “Trading volume and asset liquidity,” *The Quarterly Journal of Economics*, 1989, 104 (2), 255–274.
- Pakes, Ariel, Michael Ostrovsky, and Steven T. Berry**, “Simple Estimators for the Parameters of Discrete Dynamics Games,” *The RAND Journal of Economics*, 2007, 38 (2), 373–399.
- Radner, Roy and Joseph Stiglitz**, “A Nonconcavity in the Value of Information,” *Bayesian models in Economic Theory*, 1984, 5, 33–52.
- Rust, John**, “Optimal replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher,” *Econometrica*, 1987, 55 (5), 999–1033.
- Ryan, Stephen P.**, “The Costs of Environmental Regulation in a Concentrated Industry,” *Econometrica*, 2012, 80 (3), 1019–1062.
- Schultz, Paul**, “The market for new issues of municipal bonds: The roles of transparency and limited access to retail investors,” *Journal of Financial Economics*, 2012, 106 (3), 492–512.
- Wang, Junbo, Chunchi Wu, and Frank X. Zhang**, “Liquidity, default, taxes, and yields on municipal bonds,” *Journal of Banking & Finance*, 2008, 32 (6), 1133–1149.
- Weintraub, Gabriel Y., C. Lanier Benkard, and Benjamin Van Roy**, “Markov perfect industry dynamics with many firms,” *Econometrica*, 2008, 76 (6), 1375–1411.

Appendix

A Additional Tables and Figures

	Sales Trade Size			Purchases Trade Size		
	6 Months	9 Months	12 Months	6 Months	9 Months	12 Months
uninsured * $\mathbb{I}\{t > t_0\}$	-6.145 (7.222)	-2.346 (3.898)	-1.665 (3.297)	-5.213 (4.420)	-7.674 (5.946)	-6.713 (5.054)
N Level	289,886	476,903	640,087	320,509	429,568	451,482

Table 8: Difference-in-Difference Estimates of Transparency on Trade Size

Group	Baseline Specification		Instrumented Version	
	β	δ	β	δ
I	-0.0008	0.849	-0.0002	0.249
II	-0.0116	0.948	-0.0003	0.634
III	-0.0005	0.763	0.00012	0.601
IV	-0.0006	0.829	-0.0001	0.667
V	-0.0001	0.903	-0.0002	0.236
VI	-0.0023	0.616	-0.0007	0.288
VII	-0.0003	0.255	-0.0002	0.252
VIII	-0.0006	0.257	-0.0004	0.752
IX	-0.0007	0.321	-7.92e-	0.815
X	-0.0016	0.572	-0.0006	0.255
XI	-0.0007	0.348	-0.0007	0.274
XII	-0.0008	0.232	-0.0010	0.397
XIII	-0.0005	0.964	-0.0137	0.887
XIV	-0.0006	0.276	-0.0008	0.969
XV	-0.0025	0.368	-0.0010	0.958
XVI	-0.0010	0.791	-0.0016	0.289

Table 9: Estimates for Experience

B What do Dealers Know?

We use the specification test suggested in Dickstein and Morales (2015) to test the assumption that dealers have no information about the market value of the asset in months where they don't participate to trade. The intuition behind the test is the following: let $y_{d,t}$ be an outcome variable that depends on a decision of dealer d in period t , such as the quantity traded in a certain asset, or the price charged to investors. Let also $\mathcal{I}_{d,t}$ denote dealer d 's information set at the beginning of period t . Dealer d 's decision about $y_{d,t}$ will depends on dealer d 's expectation of the market value for the asset $\mathbb{E}(\theta_t|\mathcal{I}_{d,t})$, conditional on what he knows about past realizations of θ_t . Under this scenario, if a variable Z_t belongs to d 's information set $\mathcal{I}_{d,t}$, then it must be orthogonal to his forecast error:

$$\mathbb{E}[(\theta_t - \mathbb{E}(\theta_t|\mathcal{I}_{d,t})) Z_t] = 0.$$

In this case, therefore, Z_t would be a instrument for $\mathbb{E}(\theta_t|\mathcal{I}_{d,t})$ in the regression

$$\begin{aligned} y_{d,t} &= \alpha + \beta\theta_t + \beta(\mathbb{E}(\theta_t|\mathcal{I}_{d,t}) - \theta_t) \\ &= \alpha + \beta\theta_t + \epsilon_{d,t} \end{aligned}$$

We use this idea to test whether the dealer knows the average market price for asset that he does not trade in a given month. Table 10 reports the result of this test for different outcome variables $y_{d,t}$ and instruments Z_t . The first two column test whether the dealer knows the average trading price of an asset in periods in which he does not trade. In all four of the combinations the p -value is zero, suggesting that the average price for the asset, $\theta_{t,a}$, or for assets from the same state $\theta_{t,s}$, don't belong to the dealer's information set when he does not trade. On the contrary, for periods in which the dealers did participate to trade the test cannot reject the null, confirming that dealer d acquire information through trade.

	$y_{d,t} = n_{d,t}^+$	$y_{d,t} = n_{d,t}^-$
$(1 - \mathbb{I}\{\text{trade in } t - 1\})\theta_{t-1,a}$	0.00	0.00
$(1 - \mathbb{I}\{\text{trade in } t - 1\})\theta_{t-1,s}$	0.00	0.00
$\mathbb{I}\{\text{trade in } t - 1\}\theta_{t-1,a}$	0.02	0.75
$\mathbb{I}\{\text{trade in } t - 1\}\theta_{t-1,s}$	0.10	0.15

Table 10: p-values for Hansen-Sargan test

C Definition of Θ

Below we outline the steps we follow to recover Θ . For every month t we compute the average trading price in trades between dealers and investors. Let \hat{p}_t^+ be the average price at which dealers buy the asset, and \hat{p}_t^- be the average price at which dealers sell the asset. According to our model, as the number of

trades i increases,

$$\begin{aligned}\hat{p}_t^+ &= \frac{1}{N} \sum p_{it}^+ \rightarrow \mathbb{E}(p_t^+ | \theta_t) = \int p f(p | \theta_t, +) dp. \\ \hat{p}_t^- &= \frac{1}{N} \sum p_{it}^- \rightarrow \mathbb{E}(p_t^- | \theta_t) = \int p f(p | \theta_t, -) dp.\end{aligned}$$

To recover the underlying sequence for the parameter θ_t and its transition matrix h we fit a Normal Hidden Markov Model with three states to the sequence of market prices $\hat{p}_t = \frac{1}{2} (\hat{p}_t^+ + \hat{p}_t^-)$.

Concretely, we use an EM algorithm to select transition matrix \hat{h} and initial probability \hat{h}_0 to maximize the expected log-likelihood

$$\mathbb{E} [l_T(p_{1:T}, \theta_{1:T} | h, h_0, \mu_\theta, \sigma_\theta)],$$

where

$$l_T(p_{1:T}, \theta_{1:T} | h, h_0, \mu_\theta, \sigma_\theta) = \log h_0(\theta_1) + \sum_{t=2}^T \log h(\theta_t | \theta_{t-1}) + \sum_{t=2}^T \log \left(\frac{1}{\sigma_{\theta_t}} \phi \left(\frac{\hat{p}_t - \mu_{\theta_t}}{\sigma_{\theta_t}} \right) \right).$$

Table 11 highlights the features of the recovered parameters across different classes of assets. The three columns of the table show, for each group of assets, the average purchase and selling prices by state, $\frac{1}{T} \sum p_t \mathbb{I} \{ \theta_t = \theta^k \}$. Finally the last two columns report the average number of changes for θ_t within an year and the average value of σ_{θ_t} . The state changes around three times within an year, this is a reasonable number considering that each group includes several assets. Furthermore the bid-ask spread is on average 5%, and it is larger for lower values assets (the correlation is -65%).

Group	Average Ask Price			Average Bid Price			Changes per year	σ_{θ_t}
	θ_{high}	θ_{mid}	θ_{low}	θ_{high}	θ_{mid}	θ_{low}		
I	1.02	1.038	1.053	0.997	1.014	1.03	4.06	0.015
II	0.701	0.738	0.776	0.707	0.714	0.727	1.029	0.038
III	1.007	1.017	1.026	0.989	0.995	1	3.383	0.015
IV	1.063	1.08	1.094	1.05	1.068	1.08	3.14	0.015
V	0.997	1.015	1.031	0.972	0.987	1.003	3.549	0.015
VI	1.044	1.049	1.054	1.029	1.035	1.04	3.071	0.014
VII	0.901	0.932	0.974	0.855	0.898	0.933	2.057	0.041
VIII	1.067	1.076	1.082	1.056	1.064	1.07	3.913	0.015
IX	0.949	0.98	0.997	0.911	0.943	0.957	1.662	0.029
X	0.948	0.964	0.983	0.914	0.931	0.945	2.903	0.017
XI	1.048	1.06	1.072	1.03	1.04	1.051	2.967	0.015
XII	0.801	0.82	0.837	0.778	0.796	0.813	3.429	0.021
XIII	1.029	1.03	1.036	1.012	1.013	1.017	3.086	0.014
XIV	0.975	0.993	1.018	0.943	0.963	0.983	3.464	0.013
XV	1.097	1.118	1.135	1.088	1.109	1.126	3.338	0.017

Table 11: Estimates of Θ

D Assets Classes

For the purpose of the estimation, we divide assets $j = \{1, \dots, N_{\text{asset}}\}$ traded in the secondary market for municipal bonds into 15 groups, $a \in \{1, \dots, 15\}$. Denote by $\bar{p}_{j,t}$ the average selling price asset j and denote by $\bar{p}_{a,t}$ the average selling price for assets belonging to class a in month t

$$\bar{p}_{a,t} = \frac{1}{N_a} \sum p_{i,t}.$$

Ideally the assignment of assets to classes should satisfy two conditions. First, for every class a past prices should have strong predictive power for the current price, hence $\text{Cov}(\bar{p}_{a,t}, \bar{p}_{a,t-k})$ should be large. Moreover, knowing past trading price for class a' , $\bar{p}_{a',t-k}$, should not help in predicting $\bar{p}_{a,t}$, conditional on the realization of the current public signal y_t^P .

To define classes that satisfy these conditions, we modify a standard k-means algorithm. Denote by $\mu^*(j) \in \{1, \dots, 15\}$ the assignment of assets to classes. The algorithm follows these steps.

1. First we define a random assignment of assets $\mu^{(0)}$
2. To evaluate any assignment $\mu^{(m)}$ we first compute average prices within each class

$$\bar{p}_{a,t}^{(m)} = \frac{1}{N_a^{(m)}} \sum P_{\mu^{(m)}(j)=a,t},$$

estimate the regression

$$\bar{p}_{a,t}^{(m)} = \rho_0 + \rho_1 \bar{p}_{a,t-1}^{(m)} + \rho_2 y_t^P + \epsilon, \quad (21)$$

3. Finally, we use 21 to update assignment $\mu^{(m)}$. In particular, $\mu^{(m+1)}(j)$ is defined as

$$\mu^{(m+1)}(j) = \arg \min_a \sum_t \left(\bar{p}_{j,t} - p_{a,t}^{(0)} - \hat{\rho}_0 - \hat{\rho}_1 \bar{p}_{a,t-1}^{(0)} - \hat{\rho}_2 y_t^P \right)^2.$$

Table 12 reports some characteristics of the different classes of assets. In particular, for the second column, we estimate separate regressions

$$\bar{p}_{a,t}^{(m)} = \rho_0 + \rho_{1,a'} \bar{p}_{a',t-1}^{(m)} + \rho_2 y_t^P + \epsilon,$$

and report the average p-value of the coefficients $(\rho_{1,a'})_{a' \neq a}$. Furthermore, for the third column, we estimate the regression

$$\bar{p}_{a,t}^{(m)} = \rho_0 + \rho_{1,a} \bar{p}_{a,t-1}^{(m)} + \rho_2 y_t^P + \epsilon,$$

and report the p-value associated to coefficient $\rho_{1,a}$.

Group	N. of assets	Total Volume of Trade (\$10 ⁹)	$\rho_{1,a'}$	$\rho_{1,a}$
I	18,715	57.664	.377	.040
II	8,356	41.47	.539	.011
III	14,599	42.52	.586	0.001
IV	1,638	7.52	.456	0.215
V	14,876	87.99	.348	0
VI	14,371	61.86	.379	0
VII	17,145	59.44	.437	0
VIII	308	6.65	.327	0
IX	8,955	50.08	.383	0
X	1,275	11.87	.430	0
XI	19,266	65.72	.489	0.01
XII	1,952	6.08	.381	0
XIII	22,590	50.01	.541	0
XIV	9,516	90.39	.552	0.008
XV	7,498	87.65	.342	0

Table 12: Classes of Assets.

E Choice Probabilities

We assume that: (i) cost shocks $(\epsilon_{d,t}^{\text{buy}}, \epsilon_{d,t}^{\text{sell}}, \epsilon_{d,t}^{\emptyset}) \in \mathbb{R}^3$, are drawn from a double exponential distribution F_0 , with standard deviation σ_0 ; (ii) $\epsilon_{d,t}^1 \in \mathbb{R}$ is drawn from a normal distribution F_1 with standard deviation σ_1 ; (iii) $\tilde{c}(n) = c_1 |n| + c_2 n^2$ is convex in $|n|$; and (iv) experience transition matrix r can be rewritten as

$$r(e'|e, n, \tilde{e}) = \sum_{e''} r_{\text{d2d}}(e'|e'', \tilde{e}) r_{\text{inv}}(e''|e, n),$$

where r_{d2d} and r_{inv} describe, respectively, the change in experienced that can be attributed to inter-dealer trade trade with investors.

Denote by $V^{\text{sign}(n)}(\pi, x, e, \epsilon^1)$ the dealer's highest utility conditional on either buying or selling the asset:

$$V^{\text{sign}(n)}(\pi, x, e, \epsilon^1) = \max_{n \in \mathcal{N}(\text{sign}(n))} \left\{ -\tilde{c}(n) - \epsilon_1 |n| - \mathbb{E} \left(\sum_{i=1}^{|n|} p_{it} | \pi, \text{sign}(n) \right) + \mathbb{E} [W(\mathcal{L}_{\text{inv}}(\pi, \vec{p}_{n,t}), x'(n; x), r_{\text{inv}}(n, e))] \right\},$$

where

$$\mathcal{N}(\text{sign}(n)) = \begin{cases} \{1, \dots, N\} & \text{sign}(n) = +1 \\ \{-x, \dots, -1\} & \text{sign}(n) = -1 \end{cases},$$

The probability that dealer d chooses to trade with $n \neq 0$ investors can be written as

$$P(n_{d,t} = n | \pi, x, e) = \int_{\text{lb}(\pi, x, e, n)}^{\text{ub}(\pi, x, e, n)} \frac{\exp\left(\frac{V^{\text{sign}(n)}(\pi, x, e, \epsilon^1) - W(\pi, x, e)}{\sigma_0}\right)}{\exp\left(\frac{V^{\text{sign}(n)}(\pi, x, e, \epsilon^1) - W(\pi, x, e)}{\sigma_0}\right) + \exp\left(\frac{V^{\text{sign}(n)}(\pi, x, e, \epsilon^1) - W(\pi, x, e)}{\sigma_0}\right) + 1} dF_1(\epsilon^1),$$

where $\text{ub}(\pi, x, e, n)$ and $\text{lb}(\pi, x, e, n)$ are optimal policy thresholds defined below. Consider $n > 0$ and let $\Delta(\pi, x, e, n)$ denote the difference in the value function between buying n and $n + 1$ units:

$$\begin{aligned} \Delta(\pi, x, e, n) &= \tilde{c}(n+1) - \tilde{c}(n) - \mathbb{E}(p_{it} | \pi, +1), \\ &+ \beta \mathbb{E} \left[W(\mathcal{L}_{\text{inv}}(\pi, \vec{p}_{n+1}), x'(n+1; x), r_{\text{inv}}(n+1, e)) - W(\mathcal{L}_{\text{inv}}(\pi, \vec{p}_n), x'(n; x), r_{\text{inv}}(n+1, e)) \right]. \end{aligned}$$

Then

$$\sigma_1 \text{lb}(\pi, x, e, n) = \begin{cases} \Delta(n) & n = 1, \dots, N-1 \\ -\infty & n = N \end{cases},$$

while

$$\sigma_1 \text{ub}(\pi, x, e, n) = \begin{cases} \Delta(n-1) & n = 2, \dots, N \\ \infty & n = 1 \end{cases}.$$

In the same fashion, consider $n < 0$ and let $\Delta(\pi, x, e, n)$ denote the difference in the value function

between selling n and $n + 1$ units:

$$\begin{aligned} \Delta(\pi, x, e, n) &= \tilde{c}(n-1) - \tilde{c}(n) + \mathbb{E}(p_{it}|\pi, -1), \\ &+ \beta \mathbb{E} \left[W(\mathcal{L}_{inv}(\pi, \vec{p}_{n-1}), x'(n-1; x), r_{inv}(n-1, e)) - W(\mathcal{L}_{inv}(\pi, \vec{p}_n), x'(n; x), r_{inv}(n-1, e)) \right]. \end{aligned}$$

Then

$$\sigma_{1\text{lb}}(\pi, x, e, n) = \begin{cases} \Delta(n) & n = -1, \dots, -x-1 \\ -\infty & n = -x \end{cases},$$

while

$$\sigma_{1\text{ub}}(\pi, x, e, n) = \begin{cases} \Delta(n-1) & n = -2, \dots, -x \\ \infty & n = -1 \end{cases}.$$

F Estimation Algorithm

1. Guess an initial set of parameters τ .
2. Solve for the dealers' value functions. This requires setting an initial value $V_{(0)}$. Then, at each iteration m and until convergence
 - (a) Using the observed distribution of beliefs, experience, and inventory recovered in Section 5.2, update $W_{(m)}^{\text{buy}}$ according to

$$\begin{aligned} W_{(m)}^{\text{buy}}(\pi, x, e) &= \mathbb{P}(\tilde{e} = 0|\pi, x, e) \beta \mathbb{E} [V_{(m)}(\pi, x, g_2(0; e))] - \hat{\mathbb{E}}(\tilde{q}|\pi, x, e) + \\ &+ \sum_{\tilde{e}=1}^{\bar{E}} \mathbb{P}(e, \tilde{e}) \int \beta \mathbb{E} [V_{(m)}(\mathcal{L}_{\text{buy}}(\tilde{y}, \tilde{q}, e, \tilde{e}), x', g_2(\tilde{e}; e)) | e, \tilde{e}, \tilde{q}] \hat{f}_q(\tilde{q}|\tilde{e}, \pi, x, e) d\tilde{q}. \end{aligned}$$

Note that $\hat{\mathbb{E}}(\tilde{q}|\pi, x, e)$ is the actual average price at which a dealer in state (π, x, e) buys the asset. Similarly, we use the observed distribution of accepted offers \hat{f}_q and observed matching

probabilities $\mathbb{P}(e, \tilde{e})$.

(b) Update $\tilde{W}_{(m)}^{\text{sell}}$:

$$\begin{aligned} & \tilde{W}_{(m)}^{\text{sell}}(\pi, x, e, \tilde{e}) \\ &= \max_q \mathbb{P}_{(m)}(q \text{ is accepted} | e, \tilde{e}) \beta \mathbb{E} [V_{(m)}(\mathcal{L}_{\text{sell}}(\tilde{y}, q, e, \tilde{e}), \tilde{x}', g_2(\tilde{e}; e) | e, \tilde{e}, q)] \\ &+ \mathbb{P}_{(m)}(q \text{ is rejected} | e, \tilde{e}) \beta \mathbb{E} [V_{(m)}(\pi, x, g_2(0; e))], \end{aligned}$$

(c) Update $W_{(m)}^{\text{sell}}$:

$$W_{(m)}^{\text{sell}}(\pi, x, e) = \sigma_v \log \left(\sum_{\tilde{e}=1}^{\bar{E}} \exp \left(\frac{-c(\tilde{e}) + \tilde{W}_{(m)}^{\text{sell}}(\pi, x, e, \tilde{e})}{\sigma_v} \right) + \exp \left(\frac{\beta \mathbb{E} [V_{(m)}(\pi, x, g_2(0; e))]}{\sigma_v} \right) \right) + \sigma_v \gamma.$$

(d) Update $W_{(m)}$:

$$W_{(m)} = \alpha W_{(m)}^{\text{sell}} + (1 - \alpha) W_{(m)}^{\text{buy}}.$$

(e) Update $V_{(m+1)}$:

$$\begin{aligned} & V_{(m+1)}(\pi, x, e) \\ &= -\kappa(x) + \mathbb{E} \left(\max_{n \in \{-x, \dots, 0, 1, \dots, N\}} \left\{ \begin{array}{l} -c(n, \epsilon) - \text{sign}(n) \mathbb{E} \left(\sum_{i=1}^{|n|} p_{it} | \pi, \text{sign}(n) \right) \\ + \mathbb{E} [W(\mathcal{L}_{\text{inv}}(\pi, (p_i)_{i=1}^n, \text{sign}(n)), x'(n; x), g_2(|n|; e))] \end{array} \right\} \right). \end{aligned}$$

3. Compute optimal choice probabilities according to (7) and (11), and simulate choices $\left\{ \mathbb{I}_{d,t,\tilde{e}}^{(m)}, \mathbb{I}_{d,t,\tilde{e}}^{(m)} \right\}_{m=1}^M$.
4. For each simulated sample, find the auxiliary parameters that maximize $\mathcal{L}(\tilde{\mathbb{I}}; \alpha, \beta, z)$.

G Steady-State conditions

Let f_{inv}^* denote the distribution of dealers' private history after trade with investors implied by f^* . Then, f_{inv}^* satisfies

$$\begin{aligned} & f_{\text{inv}}^*(\pi_d \in A_\pi, x_d \in A_x, e_d \in A_e | \theta) \\ &= \sum_{n=-N}^N \int \left(\int \mathbb{I}_{A(\vec{p}_n)} f(\vec{p}_n | \theta, \text{sign}(n)) d\vec{p}_n \right) P(n | \pi_d, x_d, e_d) f^*(\pi_d, x_d, e_d) d(\pi_d, x_d, e_d), \end{aligned}$$

where

$$A(\vec{p}_n) = \{\mathcal{L}_{inv}(\pi_d; \vec{p}_n, \text{sign}(n)) \in A_\pi, x_d - n \in A_x, r_{inv}(e_d, n) \in A_e\},$$

the probability that dealer d chooses n , $P(n|\pi_d, x_d, e_d)$, is defined in 7, and \mathcal{L}_{inv} is defined in 3.

Next, let $f_q^*(q \in A_q|e, \tilde{e}, \theta)$ be the equilibrium distribution of offers directed from a seller of type e to a buyer of type \tilde{e} , in state θ . Then

$$f_q^*(q \in A_q|e, \tilde{e}, \theta) = \int \int \mathbb{I}\{q(\pi_d, x_d, e_d, \tilde{e}) \in A_q\} f_{inv}^*(\pi_d, x_d, e_d|\theta, P_e(\pi_d, x_d, e_d, \xi) = \tilde{e}) d(\pi_d, x_d, e_d) d\xi,$$

where $q(\cdot)$ achieves the maximum in (9), and $P_e(\cdot)$ solves (10).

Finally, define $f_r^*(r|e, \tilde{e}, \theta, q)$ to be the equilibrium probability that an offer q receives reply $r \in \{0, 1\}$, conditional on the seller having experience e , the buyer having experience \tilde{e} , and the state being θ :

$$f_r^*(\bar{r}|e, \tilde{e}, \theta, q) = \int \int \mathbb{I}\{r(\pi_d, x_d, e, \tilde{e}, q) = r\} f_{inv}^*(\pi_d, x_d|\theta, e_d = e) d(\pi_d, x_d),$$

where $r(\cdot)$ achieves the maximum in (8).

Then the steady state distribution f^* must satisfy

$$\begin{aligned} f^*(\pi_d \in A_\pi, x_d \in A_x, e_d \in A_e|\theta) &= \alpha f_{sell}^*(\pi_d \in A_\pi, x_d \in A_x, e_d \in A_e|\theta) \\ &\quad + (1 - \alpha) f_{buy}^*(\pi_d \in A_\pi, x_d \in A_x, e_d \in A_e|\theta), \end{aligned}$$

where $f_{sell}^*(\cdot|\theta)$ and $f_{buy}^*(\cdot|\theta)$ are the distributions of the state among potential buyers and sellers, after inter-dealer trade. In particular

$$\begin{aligned} &f_{sell}^*(\pi_d \in A_\pi, x_d \in A_x, e_d \in A_e|\theta) \\ &= \sum_{\tilde{e}=1}^{\bar{E}} \int \int \mathbb{I}_{A_{sell}}(\pi_d, x_d, e_d, \tilde{e}, r, q) f_r^*(r|e_d, \tilde{e}, \theta, q) f_q^*(q|e_d, \tilde{e}, \theta) P(\tilde{e}|\pi_d, x_d, e_d) f_{inv}^*(\pi_d, x_d, e_d) d(\pi_d, x_d, e_d) \\ &\quad + \int \mathbb{I}_{A_{no\ trade}} P(0|\pi_d, x_d, e_d) f_{inv}^*(\pi_d, x_d, e_d|\theta) d(\pi_d, x_d, e_d), \end{aligned}$$

where

$$A_{\text{no trade}} = \{\pi_d \in A_\pi, x_d \in A_x, e_d \in A_e\},$$

$$A_{\text{sell}}(\pi_d, x_d, e_d, \tilde{e}, r, q) = \{\mathcal{L}_{\text{sell}}(\pi_d, r, q, e_d, \tilde{e}) \in A_\pi, x_d - r \in A_x, r_{\text{d2d}}(e_d, \tilde{e}) \in A_e\},$$

and $f_{\text{buy}}^*(\cdot|\theta)$ can be defined similarly.

H Proofs from Section 5

Proof of Lemma 1. First rewrite

$$\begin{aligned} c_t(\delta) &= \sum_{k \geq 1} \delta^k I_{t,t-k} \\ &= \delta \alpha g_t n_{t-1} + \delta^2 \alpha^2 g_t g_{t-1} n_{t-2} \dots \\ &= \delta \alpha g_t \left(n_{t-1} + \sum_{k \geq 2} \delta^{k-1} \alpha^{k-1} g_{t-1} \dots n_{t-k} \right). \end{aligned}$$

Next, note that

$$\begin{aligned} r_t &= n_{t-1} + \delta \alpha g_{t-1} (n_{t-2} + \delta \alpha g_{t-2} r_{t-2}) \\ &= n_{t-1} + \delta \alpha g_{t-1} n_{t-2} \\ &\quad + \delta^2 \alpha^2 g_{t-1} g_{t-2} (n_{t-3} + \delta \alpha g_{t-3} r_{t-3}) \\ &= \dots \\ &= n_{t-1} + \sum_{k \geq 2} (\delta \alpha)^{k-1} g_{t-1} \dots g_{t-k} n_{t-k}, \end{aligned}$$

then

$$e_t - \delta e_{t-1} = n_t + \delta \alpha g_t r_t.$$

□

Proof of Lemma 2. Simply note that the sequence $(r_t)_{t \geq 0}$, satisfies

$$\begin{aligned} r_t &= n_{t-1} + \sum_{k \geq 2} (\delta\alpha)^{k-1} g_{t-1} \cdots g_{t-k} n_{t-k} \\ &< N + \sum_{k=1}^t (\delta\alpha)^k D^k N^{k-1} \end{aligned}$$

Therefore,

$$\begin{aligned} e_t &= \sum_{k \geq 1} \delta^k \left(N + \sum_{h=1}^k (\delta\alpha)^h D^h N^{h-1} \right) \\ &= \sum_{k \geq 1} \delta^k N + \sum_{k \geq 1} \delta^k \sum_{h=1}^k (\delta\alpha)^h D^h N^{h-1} \\ &< \frac{N}{1-\delta} + \alpha D \sum_{k \geq 1} \delta^{k+1} \frac{1 - (\delta\alpha)^{k+1} D^{k+1} N^{k+1}}{1 - (\delta\alpha) DN} \\ &< \frac{N}{1-\delta} + \frac{\alpha D}{1 - (\delta\alpha) DN} \left(\frac{1}{1-\delta} - \delta^4 \alpha^2 (DN)^2 \sum_{k \geq 0} \delta^{2k} \alpha^k D^k N^k \right). \end{aligned}$$

This, in turn, is bounded if

$$\delta^2 \alpha < \frac{1}{DN}.$$

Focus on the situation of seller d who trades with buyer \tilde{d} at price $q_{d,t}$. Denote by $e_{d,t}$ and $e_{\tilde{d},t}$, respectively, dealer d and dealer \tilde{d} 's experience levels. Furthermore $\hat{\pi}_{d,t}$ and $\hat{\pi}_{\tilde{d},t}$ denote dealers d and \tilde{d} beliefs at the moment of the trade (that is, after inter-dealer trade). Dealer d observes post-trade signal $y_{\tilde{d},t} = \pi_{\tilde{d},t}$, as well as dealer \tilde{d} 's decision about whether to accept the offer, $r_{\tilde{d},t} = r(\pi_{\tilde{d},t}, x_{\tilde{d},t}, e_{\tilde{d},t}, q_{d,t}, e_{d,t})$. Dealer d 's updated belief satisfies

$$\hat{\pi}_{d,t}(\theta_t = \theta^k | \pi_{\tilde{d},t}, e_{\tilde{d},t}, q_{d,t}, e_{d,t}) = \frac{f^*(\pi_{\tilde{d},t}, r_{\tilde{d},t} | e_{\tilde{d},t}, q_{d,t}, e_{d,t}, \theta^k) \hat{\pi}_{d,t}(\theta^k)}{\sum_{\theta} f^*(\pi_{\tilde{d},t}, r_{\tilde{d},t} | e_{\tilde{d},t}, q_{d,t}, e_{d,t}, \theta) \hat{\pi}_{d,t}(\theta)}.$$

We can rewrite this as

$$\begin{aligned}
& f^* \left(\pi_{\tilde{d},t}, r \left(\pi_{\tilde{d},t}, x_{\tilde{d},t}, e_{\tilde{d},t}, q_{d,t}, e_{d,t} \right) \mid e_{\tilde{d},t}, q_{d,t}, e_{d,t}, \theta^k \right) \\
= & \int_{A_r(\pi_{\tilde{d},t}, e_{\tilde{d},t}, q_{d,t}, e_{d,t})} f^* \left(\pi_{\tilde{d},t}, x_{\tilde{d},t} \mid e_{\tilde{d},t}, \theta^k \right) dx_{\tilde{d},t},
\end{aligned}$$

where

$$A_r \left(\pi_{\tilde{d},t}, e_{\tilde{d},t}, q_{d,t}, e_{d,t} \right) = \left\{ x_{\tilde{d},t} : r \left(\pi_{\tilde{d},t}, x_{\tilde{d},t}, e_{\tilde{d},t}, q_{d,t}, e_{d,t} \right) = r \right\}$$

However information about common shock θ_t contained in inventory $x_{\tilde{d},t}$ is already incorporated in $\pi_{\tilde{d},t}$, since dealer \tilde{d} knows $x_{\tilde{d},t}$. Therefore

$$\begin{aligned}
& f^* \left(\pi_{\tilde{d},t}, x_{\tilde{d},t} \mid e_{\tilde{d},t}, \theta^k \right) \\
= & f^* \left(x_{\tilde{d},t} \mid e_{\tilde{d},t}, \pi_{\tilde{d},t} \right) f^* \left(\pi_{\tilde{d},t} \mid e_{\tilde{d},t}, \theta^k \right),
\end{aligned}$$

and

$$\begin{aligned}
& f^* \left(\pi_{\tilde{d},t}, r \left(\pi_{\tilde{d},t}, x_{\tilde{d},t}, e_{\tilde{d},t}, q_{d,t}, e_{d,t} \right) \mid e_{\tilde{d},t}, q_{d,t}, e_{d,t}, \theta^k \right) \\
= & f^* \left(\pi_{\tilde{d},t} \mid e_{\tilde{d},t}, \theta^k \right) \int_{A_r(\pi_{\tilde{d},t}, e_{\tilde{d},t}, q_{d,t}, e_{d,t})} f^* \left(x_{\tilde{d},t} \mid e_{\tilde{d},t}, \pi_{\tilde{d},t} \right) dx_{\tilde{d},t}.
\end{aligned}$$

Since the last term doesn't depend on common shock θ_t , we can rewrite

$$\hat{\pi}_{d,t} \left(\theta_t = \theta^k \mid \pi_{\tilde{d},t}, e_{\tilde{d},t}, q_{d,t}, e_{d,t} \right) = \frac{f^* \left(\pi_{\tilde{d},t} \mid e_{\tilde{d},t}, \theta^k \right) dx_{\tilde{d},t} \hat{\pi}_{d,t} \left(\theta^k \right)}{\sum_{\theta} f^* \left(\pi_{\tilde{d},t} \mid e_{\tilde{d},t}, \theta \right) \hat{\pi}_{d,t} \left(\theta \right)}.$$

□