We develop a dynamic model of dealer intermediation between a monopolistic customer-dealer (B2C) market and a competitive inter-dealer (B2B) market. Dealers face inventory constraints and adverse selection. We characterize the optimal quote setting and inventory management behavior for both markets in closed form and reveal how price setting in one market segment influences quote behavior in the other. The framework features a unique stable equilibrium for bid and ask quotes in both market segments. We show under which conditions dealer intermediation improves welfare over a spot trading venue which clears synchronous customer demand only, and how increased customer sophistication can make market breakdown more likely at high levels of price volatility. Data from the European sovereign bond market is used to illustrate some of the empirical implications.
1 Introduction

Dealers are intermediaries between different market segments. A dealer typically maintains a network of customer relationships and simultaneously participates in an inter-dealer market which allows him to manage his inventory. In the customer segment, the dealer typically has some market power because his clients face search costs and do not have direct access to the wholesale or inter-dealer market. Inter-dealer markets on the other hand are often highly competitive and have become dominated by electronic inter-dealer trading platforms. Surprisingly, much of the microstructure literature has ignored this “interface role” of the dealer and has focused on dealer behavior in a single market.¹

This paper provides a new simple framework to analyze the dealer intermediation between a monopolistic customer-dealer (B2C) market and a competitive inter-dealer (B2B) market. Dealers face inventory constraints and adverse selection. We characterize the optimal quote setting and inventory management behavior in both markets in closed form and obtain new insights into the interdependence between both market segments. We focus in particular on the adverse selection risk which is essential to dealers in financial markets. Our model is most applicable to a setting in which adverse selection risk flows from the B2C to the B2B market. Market power in the B2B segment allows dealers to charge monopolistic price mark-ups and absorb the adverse selection risk from client transactions. But whenever they access the B2B market in order to rebalance their inventory, dealers pass on this adverse selection risk to the highly competitive B2B platform where it becomes the key component of spread determination. Via inventory rebalancing, B2B spread become highly informative about adverse selection risk.

But there is also an important feedback effect from the B2B market to the B2C market. Higher B2C spreads obviously increase the costs of inventory rebalancing. Dealers adjust by making their B2C quotes more inventory contingent—a behavior called "inventory shading". As a consequence, the dispersion of B2C transaction prices increases as well as the average B2C spread. Higher B2C spread in turn may aggravate the adverse selection problem as only the most informative client orderflow gets executed. In conclusion, adverse selection risk from the B2C market concentrates via inventory rebalancing in the B2B market and determines B2B spreads, which in turn influence inventory shading, B2C price dispersion, as well as the average B2C spread and thereby the adverse selection component of the client order flow. Our model captures this essential feedback loop of market intermediation in

¹Modelling dealer quote behavior has proven difficult in a single market so that issues of market interdependence between wholesale and customer segment appear even more intractable. A second reason is empirical; financial data is abundantly available for inter-dealer markets, but rare for both the inter-dealer and customer segments simultaneously.
a parsimonious way with closed form solutions.

The model also speaks to important regulatory policy issues. Trading (or order processing) costs in the B2B platform may depend on the market power of the central counterparty (CCP), which charges order processing fees on its trading platform. Any security transaction tax (STT) should also increase order processing costs. How is the overall market quality affected by such increases in the B2B order processing costs? We can highlight two important effects. First, higher order processing cost get fully reflected in the competitive B2B spreads and increase the inventory rebalancing costs for the dealers. This increases both the dispersion of B2C transaction prices and the average spread in the B2C market. Second, a higher average B2C spread makes client order flow more informative, aggravates the adverse selection problem for the dealers, and generates B2B market breakdown at lower levels of market volatility. Low cost access to the B2B trading platform is therefore a requisite for a robust market structure in a two-tier market and should be a key regulatory concern.

A second important regulatory issue concerns the desirability of the two tier market structure relative to fully integrated trading which dispenses with dealer intermediation. We can show under what conditions market intermediation provides higher customer welfare compared to pure spot trading venue in which only simultaneous trading needs are matched. Essentially, infrequent customer arrival combined with a need for trade immediacy gives a clear welfare benefit to the inter-dealer structure compared to pure spot trading which suffers from the intertemporal double coincidence of trading needs. In contrast we can show that, under a very high rate of customer arrival, a centralized spot trading venue provides higher welfare benefits.

A shortcoming of our baseline model is the monopolistic market structure in the B2C segment, which ties each customer to a single dealer and prevents the former from shopping for better quotes. We therefore extend the framework by assuming that only a share of customer is captured by a dealer, while the remaining group consists of sophisticated customers shopping for the best deal among all dealers. Sophisticated customers undertake transactions only with those dealers which —due to inventory imbalances— feature the most at the most favorable reservation prices and such customers also extract all the transaction rents. We interpret a higher share of sophisticated clients as a more competitive B2C market structure and explore its effects on market quality.

2 Market quality in the European Bond Market

The empirical part of the paper illustrates key model implications based on new data from the European sovereign bond market. The latter is the world’s largest bond market and corresponds to the
two tier structure: primary dealers have access to an inter-dealer market and simultaneously manage customer relationships with many institutional clients. During the financial crisis this market has seen repeated market breakdown as indicated by extremely low trading volumes. Figure 1 illustrates such market liquidity shortfalls as dark (light) shaded periods during the recent European sovereign debt crisis. The market breakdown for Portuguese, Greek, and Irish 10-year benchmark bonds coincides (unlike for German bonds) with a considerable increase in realized volatility for the respective bonds. The dealership structure of the European bond market is therefore fragile. The repeated and prolonged market breakdown suggests that adverse selection is an important aspect of this dealer market in line with our modeling setup.

To further explore the empirical validity of the proposed framework, we use a new data set which matches quoted and executed prices from the B2C segment to the prevailing best price in the B2B segment. This synchronized price data allows us to benchmark B2C execution quality against the corresponding quotes in the B2B market. Based on an exact measurement of market quality in both market segments we can test a number of hypothesis which are specific to our model of dealer intermediation.

First, trading of different bond maturities by the same sovereign issuer allows us to examine the role of adverse selection risk proxied by the varying interest rate risk of different bond maturities. In our dealer model, adverse selection risk in the B2C market is partly absorbed by the dealers and passed on to B2B market, where it gets fully impounded in spreads. Large B2B spreads in turn increase dealer inventory management costs (i.e. the cost of rebalancing) and increase B2C price dispersion. We find evidence for both effects in bonds sorted by maturity: Long-run bonds show on average five times larger B2B spreads than short-medium bonds and also roughly five times more B2C price dispersion. The strong duration dependence of B2C price dispersion shows that price discrimination across customer types (Green, et al. (2007)) alone is unlikely to provide a satisfying explanation for the observed bond price heterogeneity in the European sovereign bond market.

Second, the two-tier structure of the European bond market provides more direct evidence for the inventory dependence of B2C market quality. According to our intermediation model, aggregate inventory imbalances of the dealers are reflected in limit order imbalances in the B2B platform. We can show that such aggregate dealer inventory imbalances (proxied by B2B limit order imbalances) strongly influence market quality positively on the B2C ask-side and negatively on the B2C bid-side. A two standard deviation increase in the imbalance variable improves ask-side B2C transactions by 0.42 basis points and deteriorates bid-side B2C transactions by 0.30 basis points.
3 Related Literature

The early microstructure literature on dealer behavior has recognized the importance of both adverse selection (Glosten and Milgrom (1985), Kyle (1985)) and inventory management concerns (Stoll (1978), Amihud and Mendelson (1980)) for quote determination. Subsequent work integrated both aspects into dynamic models with a (single) value optimizing dealer (O’Hara and Oldfield (1986), Madhavan and Smidt (1993)). In Madhavan and Smidt (1993), a ‘specialist’ sets quotes to trade with informed and liquidity traders and simultaneously faces inventory costs. A single market serves the purpose of both customer intermediation and inventory management. Hendershott and Menkveld (2010) single dealer dynamic inventory management model relates inventory positions to short-run price pressure effects. Our work differs in its focus on dealer intermediation between markets. We are aware of no other paper which provides an integrated analysis of both B2B and B2C markets.

Studies of customer price quality are still rare even though most investors do not have direct access to an inter-dealer market. Recently, work on retail prices in the U.S. municipal bond market has aroused considerable interest (Harris and Piwowar (2006), Green et al. (2007)). This over-the-counter market lacks the price transparency of the European bond market and liquidity is dispersed over a large number of bonds. Dealer intermediation in the U.S. municipal bond market results in a large retail price dispersion and very unfavorable retail prices for many small investors. Green et al. (2007) explain the retail price dispersion in the U.S. bond market by reference to dealer price discrimination against uninformed small retail customers. In a study of the UK gilt market, Vitale (1998) also finds results which sharply contrast with ours. In his study, he finds that imbalances in inventories do not condition the transaction price set by market-makers. He also finds transaction costs in the inter-dealer market are substantially smaller than those for external customers. By ‘customer’ he means any one who is not a member of the London Stock Exchange. Our B2C data on European sovereign bonds concerns larger financial investors with access to the electronic quote request system. It is important to emphasize that our B2C market is a market between dealers and sophisticated financial customers rather than a ‘retail’ market in which private households transact. But this makes it all the more surprising that the B2C market in the European sovereign bonds also features large price dispersion and points to dealer inventory concerns as an important alternative explanation.

\[\text{Evidence that higher post-trade transparency lowers trading costs is found for the corporate bond market in a variety of studies (Bessembinder et al. (2006), Edwards et al. (2007), Goldstein et al. (2007)).}\]

\[\text{In this respect the B2C market in Euro-area sovereign bonds is more akin to how institutional block orders execute in equity dealer markets (Reiss and Werner (1996), Bernhardt et al. (2005)). It is also less plausible to interpret any price differences between the B2B and B2C transactions as ‘trading errors’.}\]

4
The following section presents the dynamic model of dealer intermediation under inventory constraints. Section 5 presents a welfare analysis for the two-tier market structure relative to a pure centralized spot trading venue. Section 6 extends the analysis to different customer types. The empirical part applies the model to the European bond market. Market quality is examined (i) by bond liquidity in section 7.3, (ii) by bond maturity in section 7.4, and (iii) as a function of aggregate inventory imbalances and market volatility in section 7.5. Section 8 discusses possible extension and limitations of the analysis followed by concluding remarks in Section 9.

4 A Model of Cross-Market Intermediation

Most financial markets feature a dual market structure in which dealers maintain a network of client relationships (B2C) and have access to an inter-dealer (B2B) trading platform. Clients are excluded from participation in the B2B market and have to transact directly with a dealer. Dealer intermediation thus occurs across market segments of different competitiveness. The inter-dealer market is typically highly competitive, whereas client relationships and client search costs might provide the dealer with some market power in the dealer customer segment. The previous microstructure literature has stressed both adverse selection and inventory management concerns as important aspects of the dealership problem. Our model captures the adverse selection risk by a time varying distribution of customers’ private asset values, which are observed by dealers only with a one-period delay. Inventory management concerns are embodied simply as binding constraints on dealer inventory positions. For simplicity, dealer inventories cannot exceed these exogenous thresholds.

It is important for the tractability of the model that a dealer’s market power in the B2C segment is exogenously determined by the distribution of customer reservation prices. This means that customers do not behave strategically in our setup - for example by shopping for better dealer services. This aspect certainly ignores an important aspect of inter-dealer competition for clients. However, we relax this assumption in section 6.

4.1 Assumptions

Dealers face a stochastic arrival process for potential customers with uncertain private values. The customer arrival process has the following structure:

Assumption 1: Customer Arrival and their Reservation Prices

5
Each period a dealer faces customer requests for buy (sell) quotes with a constant probability \( q \). Let \( R^a \) and \( R^b \) denote the private customer values such that the customer buys if \( R^a > \hat{a} \) and sells if \( R^b < \hat{b} \), where the requested ask and bid prices \((\hat{a}, \hat{b})\) are set one period ahead. Private customer values have a uniform distribution with density \( d \) over the interval \([x_{t+1}, x_{t+1} + \frac{1}{d}]\) and \([x_{t+1} - \frac{1}{d}, x_{t+1}]\) for the ask and the bid, respectively. The mid-price \( x_{t+1} \) is a stochastic martingale process known to all dealers only at time \( t + 1 \).

For simplicity we choose \( \Delta x_{t+1} = x_{t+1} - x_t \in \{-\epsilon, +\epsilon\} \) with corresponding probabilities \((\frac{1}{2}, \frac{1}{2})\) and assume an upper bound for volatility with \( \epsilon < \tau \). All transactions concern a quantity of one unit.

Assumption 1 characterizes the competitive situation of each dealer in the B2C market segment. More unfavorable client quotes reduce (linearly) the chance of customer acceptance. The customer arrival probability \( q \) is exogenous, identical for the bid and ask side, and does not depend on a dealer’s quote quality. The martingale process \( x_t \) represents the common value component of the asset from which the private valuations of bid and ask side clients symmetrically deviate. The private value assumption implicitly grants dealers a certain degree of monopolistic market power that depends on the parameter \( d \). A smaller \( d \) increases the monopolistic rents a dealer can earn from the dealer-client relationship. The exogenous distribution of customer reservation prices excludes any strategic interaction between dealers, whereby the pricing behavior of a single dealer alters the customer demand for another dealer. Each dealer is assumed to be atomistic. We also assume that the parameter \( d \) is constant over time and does not depend on the volatility of the mid-price process. In principle, the parameter \( d \) could also differ on the ask and the bid side of the market. This would give rise to asymmetric market power on the ask and bid side and allow for a richer asymmetric distribution of B2C quote behavior. For simplicity, we focus on the symmetric case.

A second important aspect concerns the information structure. It is assumed that dealers quote optimal ask and bid prices for period \( t + 1 \) based on knowledge of the mid-price \( x_t \), but not yet based on the new realization \( x_{t+1} \). Hence dealer-quoted customer prices incorporate demand shocks only with a one-period delay. This subjects dealers to an adverse selection problem that widens spreads. The adverse selection risk increases in the variance \( \epsilon^2 \) of the midprice process \( x_t \). For simplicity we require that the shift to the reservation price distribution is bounded by \( \tau \) so that the ex ante optimal B2C quotes in all inventory states are still on the support of this distribution at time \( t + 1 \).

\[ 4 \]
It is useful to denote standardized ask and bid quotes by \( a = \hat{a} - x_t \) and \( b = \hat{b} - x_t \), respectively. Standardized quotes represent the quoted dealer prices relative to the current expected midprice \( x_t = \mathcal{E}(x_{t+1}) \). We also define cumulative density functions for the acceptance of a dealer quote as,

\[
F^a(R^a \geq \hat{a}) = F^a(R^a - x_{t+1} \geq \hat{a} - x_{t+1} = a - \Delta x_{t+1}) = 1 - ad + d\Delta x_{t+1}
\]

\[
F^b(R^b \leq \hat{b}) = F^b(R^b - x_{t+1} \leq \hat{b} - x_{t+1} = b - \Delta x_{t+1}) = 1 + bd - d\Delta x_{t+1},
\]

respectively. A higher dealer ask price \( a \), for example, reduces the quote acceptance linearly. The term \( d\Delta x_{t+1} \) captures changes in the acceptance probability resulting from the exogenous evolution of the reservation price distribution.

For the purpose of inventory management, dealers can resort to an inter-dealer market with a spread \( S = \hat{A} - \hat{B} > 0 \).

**Assumption 2: Competitive Inter-Dealer (B2B) Market**

Dealers have access to a fully competitive inter-dealer market and can (via market orders) buy inventory at the (best) ask price \( \hat{A} \) and sell at the (best) bid price \( \hat{B} \). The inter-dealer prices are cointegrated with the price process \( x_t \) with \( \hat{A} = x_t + \frac{S}{2} \) and \( \hat{B} = x_t - \frac{S}{2} \). We refer to standardized inter-dealer prices as \( A = \hat{A} - x_t = \frac{S}{2} \) and \( B = \hat{B} - x_t = -\frac{S}{2} \), respectively and assume \( \frac{S}{2} \in [0, \frac{1}{d} - 2\epsilon] \). The ask and bid (limit order) prices \( A \) and \( B \) are set competitively (i.e. equal a dealer’s reservation price) by a large number of dealers distributed across all inventory levels. Inter-dealer transactions require order processing costs of \( \tau \) per transaction for liquidity providers.

The inter-dealer market allows dealers to manage their inventory and respect their inventory constraints. Excessive long or short inventory positions can be reversed or at least stabilized at prices \( B \) and \( A \), respectively. The inter-dealer spread reflects all public dealer information about the price \( x_t \). The central counterparty (CCP) which owns the trading platform typically charges dealers a fee for executed limit. This brokerage fee reflects the market power of the CCP and is captured by the parameter \( \tau \). Security transaction taxes (STT) also increase \( \tau \) and we explore their effect on market quality.

An important aspect of the analysis is to develop the (endogenous) equilibrium spread \( S \) under a competitive inter-dealer market structure. A competitive market structure implies that identical

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5 Hereafter, the expression ‘standardized quotes’ means the deviation of the quote from the prevailing B2B mid-price.
dealers with identical inventory levels compete away all rents from liquidity provision in the inter-dealer market. Hence, perfect inter-dealer competition makes dealers indifferent to whether their limit order is executed or not. This indifference implies that inter-dealer transactions do not modify the value functions of the dealers. The optimal B2C quote behavior can therefore be solved for an exogenous B2B spread $S$ without consideration for the dealers limit order supply policy. The equilibrium B2B spread $S$ is only determined in a second step as a non-profit condition on limit order supply in the B2B segment.

**Assumption 3: Dealer Objectives and Inventory Constraints**

A dealer chooses optimal B2C quotes $(\tilde{a}, \tilde{b})$ at the ask and bid side, respectively, in order to maximize the expected payoff under an inventory constraint that limits her inventory level to the three values $I = 1, 0, -1$. She is required to liquidate any inventory above 1 or below -1 immediately in the inter-dealer market. Let $0 < \beta = \frac{1}{1+r} < 1$ denote the dealer’s discount factor for an interest rate on capital $r$. Let $n(I)$ be the number of dealers at each inventory level. We assume furthermore that the probability $q$ of customer arrival in the B2C market is sufficiently small so that $\frac{1}{2}q < \frac{n(1)}{n(-1)} < 2q$ holds.

In order to limit the number of state variables we allow for only three inventory levels. This choice greatly facilitates the exposition. Inventory constraints embody the idea that dealers work within managerially pre-set position limits during the course of trading. Considering endogenously determined trading limits might be interesting, but any given limit is unlikely to change over the microstructure horizon we are considering here. Direct empirical evidence about the role of inventory constraints in dealer markets mostly relates to equity markets (Hansch, Naik and Viswanathan (1998), Reiss and Werner (1998)).

The condition on the arrival probability is needed to ensure that dealer rebalancing at the best B2B spread is always feasible to avoid a one-sided illiquidity problem in the B2B market. For a continuum of dealers, $n(I)$ can be interpreted as the probability mass of dealers in each inventory state. In this case we have full convergence to a symmetric steady state distribution with $n(1) = n(-1)$ so that the liquidity condition is always fulfilled. For a discrete dealer set, a highly non-symmetric dealer distribution over the inventory states (with $n(1) = 0$ or $n(-1) = 0$) remains a small, but non-zero probability, which is neglected in the consecutive analysis.
We summarize the sequence of trading in Figure 2. It is assumed that all payoffs come at the end of the period and are therefore discounted. We also note that the optimal B2C quotes generally depend on inventory level as well as on the known state $x_t$ of the lagged price. The following sections characterize a dealer’s value function and optimal quote behavior.

4.2 A Dealer’s Value Function

We denote a dealer’s value function for the present value of all future expected payoffs by $V(s,x_t)$. The state variable $s = 1, 0, -1$ represents one of the three possible inventory values. Furthermore, let $p_{s,t,s_{t+1}}$ denote the transition probability of state $s_t$ in period $t$ to state $s_{t+1}$ in period $t+1$. For three states, a total of nine transition probabilities characterize the transition matrix

$$M = \begin{bmatrix} p_{12} + p_{11} & p_{10} & 0 \\ p_{01} & p_{00} & p_{0-1} \\ 0 & p_{-10} & p_{-1-1} + p_{-1-2} \end{bmatrix}.$$ 

The matrix element $p_{12} + p_{11}$ in the first row and column arises from two possible events. Starting from a maximum inventory of 1, the dealer remains in that state if she does not conduct any trades in the B2C market: we denote this probability as $p_{11}$. Alternatively, the dealer might acquire an additional unit if her bid quote is accepted by a customer. In this case, the dealer would exceed the maximum inventory level of 1 and has to off-set the excess inventory immediately in the B2B market with a sell transaction. We denote this probability by $p_{12}$. The symmetric case arises under a negative inventory level of $-1$, where we distinguish as $p_{-1-2}$ the probability of a dealer selling an additional unit with the obligation to acquire immediately one unit in the B2B market.

The transition probabilities depend on the standardized state-dependent ask quotes $a(s)$ and bid quotes $b(s)$. We can now characterize the value function for the three inventory states as

$$V(s,x_t) = \begin{bmatrix} V(1, x_t) \\ V(0, x_t) \\ V(-1, x_t) \end{bmatrix} = \max\{a(s), b(s)\} \beta \mathcal{E}_t \begin{bmatrix} V(s, x_{t+1}) + \tilde{\Lambda} \end{bmatrix}$$

where $\mathcal{E}_t$ represents the expectation operator, and $\tilde{\Lambda}$ denotes the period payoff given by

$$\tilde{\Lambda} = \begin{bmatrix} \tilde{\Lambda}(1) \\ \tilde{\Lambda}(0) \\ \tilde{\Lambda}(-1) \end{bmatrix} = \begin{bmatrix} \hat{B} - \hat{b}(1) & p_{12} + \hat{a}(1)p_{10} + rx_t \\ -\hat{b}(0)p_{01} + \hat{a}(0)p_{0-1} \\ -\hat{b}(-1)p_{-10} + \left[\hat{a}(-1) - \hat{A}\right]p_{-1-2} - rx_t \end{bmatrix}.$$ 

9
The payoff in state $s = 1$ includes the profit $\hat{B} - \hat{b}(1)$ if a dealer’s bid quote is executed (which occurs with probability $p_{12}$) and the expected profit $\hat{a}(1)p_{10}$ if the ask quote is accepted by a customer. Analogous explanations apply to the other two states. The terms $rx_t$ and $-rx_t$ capture the opportunity cost of capital for one unit of asset held (at the price $x_t$) as a positive or negative inventory position, respectively.

Next, we show that the optimal quote policy can be characterized in terms of the standardized quotes $(a(s), b(s))$ and so does not depend on the level of $x_t$. Quotes need to be optimal relative to any given level of the distribution of private customer values. In other words, dealers make their profit based on the spread; profit is not contingent on any particular price level of the underlying asset. The expected profit from a given spread should be the same independently of whether the bond price is €90 or €110. As a consequence, for a zero inventory level, the value function has to be independent of the price level, that is $V(0, x_{t+1}) = V(0, x_t) = V(0) = V$. For a positive or negative inventory level the value function is linear in the process $x_t$. Here, a higher price level for the price process implies that a positive inventory level has a correspondingly higher value function. An analogous remark can be made with respect to a negative inventory. Formally, we can characterize the dealer value function as follows:

**Proposition 1: Value Function Linearity**

The value function of the dealer is linear in price and concave in inventory levels:

\[
V(1, x_{t+1}) = V(1, x_t) + \Delta x_{t+1} = V - \nabla + x_{t+1} \\
V(0, x_{t+1}) = V(0, x_t) = V \\
V(-1, x_{t+1}) = V(-1, x_t) - \Delta x_{t+1} = V - \nabla - x_{t+1}
\]

where $V$ and $\nabla$ are two positive parameters.\(^6\)

Proof: See online Technical Appendix A on the authors’ webpage.

The value function is the discounted expected cash flow from being a dealer, i.e. of intertemporal intermediation in the B2C market and (occasionally) using the B2B market for inventory management. For the states $s = 1$ and $s = -1$ the value function $V(s, x_{t+1})$ accounts for the momentary value of the inventory given by $x_{t+1}$ and $-x_{t+1}$, respectively. We can also show that $V(-1, 0) = V(1, 0) < V(0, 0)$.

\(^6\)A necessary condition for existence is the usual transversality condition which requires that the present value of the future payoff be bounded.
This is intuitive, as the dealer is in a more favorable position with a zero inventory than with either extreme inventory state. A dealer with no inventory owns the two-way option of being able to absorb both ask and bid transactions in the customer segment without having to resort to the inter-dealer market. In the extreme inventory states, the dealer owns a one-way option. For example, with a positive inventory, a customer sell cannot be internalized and the dealer is forced into the B2B market: this reduces the value function. The parameter $\nabla$ characterizes the concavity of the value function with respect to the inventory level. It embodies a dealer’s value loss due to inventory constraints.

4.3 Optimal B2C Quotes

The first order conditions are obtained by differentiating the value function (1) with respect to the bid and ask prices $(\hat{a}(s), \hat{b}(s))$ for each inventory state $s$. The first order conditions do not depend on the price process $x_t$. The standardized quotes $(a(s), b(s))$ can be characterized only in terms of the inter-dealer spread $S$, the parameter $\nabla$, and the density parameter $d$ for the distribution of reservation prices.

For example, increasing the quoted ask price $a(1)$ in state $s = 1$ marginally by $\partial a$ has two opposite effects. It increases the expected profit on prospective sell transactions that have a likelihood of $q F^a (R^a - x_{t+1} \geq a(1) - \Delta x_{t+1} = q (1 - a(1)d + d\Delta x_{t+1})$ for the current period. This implies an expected profit increase of $q [1 - a(1)d] \partial a$. But a higher selling price also reduces the number of expected buyers by $(qd) \partial a$ and the value of each transaction is given by $a(1) + \nabla$. The marginal gain and loss are equalized for

$$q [a(1) + \nabla] d = q (1 - a(1)d),$$

which implies, for the optimal ask quote,

$$a(1) = \frac{1}{2d} - \frac{1}{2} \nabla.$$

Similar expressions are obtained for the two other inventory states and for the optimal bid quotes, which we summarize in proposition 2:

**Proposition 2: Optimal B2C Quotes**

For every given inter-dealer spread $0 < S < \frac{2}{d} - 4\varepsilon$ and inventory state $s$, there exists a unique optimal ask and bid quote $(a(s), b(s))$ given by

$$\begin{bmatrix}
a(-1) \\
a(0) \\
a(1)
\end{bmatrix} = \begin{bmatrix}
\frac{1}{2d} \\
\frac{1}{2d} \\
\frac{1}{2d}
\end{bmatrix} + \frac{1}{2} \begin{bmatrix}
S \\
\nabla \\
-\nabla
\end{bmatrix}$$

and

$$\begin{bmatrix}
b(-1) \\
b(0) \\
b(1)
\end{bmatrix} = \begin{bmatrix}
-\frac{1}{2d} \\
-\frac{1}{2d} \\
-\frac{1}{2d}
\end{bmatrix} + \frac{1}{2} \begin{bmatrix}
\nabla \\
-\nabla \\
-\frac{S}{2}
\end{bmatrix}.$$
which depend linearly on the concavity parameter $\nabla$ and the inter-dealer spread $S$. The value function of a dealer follows as the perpetuity value of her future expected payoffs $\Lambda_0$ and the expected adverse selection losses $\Phi$. Formally,

$$V(s, 0) = \begin{bmatrix} V - \nabla \\ V \\ V - \nabla \end{bmatrix} = \left( I - \beta M \right)^{-1} (\Lambda_0 + \Phi).$$  \hfill (4)

The concavity parameter $\nabla > 0$ is monotonically increasing in $S$ and monotonically decreasing in the variance $\epsilon^2$ of the mid-price process $x_t$.

Proof: See online Technical Appendix B on the authors’ webpage.

Both on the bid and ask side, the optimal B2C quotes are dispersed over a range of $\frac{1}{4} S + \frac{1}{2} \nabla$. Realized B2C bid-ask spreads vary between the inside at $a(1) - b(-1) = \frac{1}{d} - \nabla$ and the outside at $a(-1) - b(1) = \frac{1}{d} + \frac{1}{2} S$. The dispersion of B2C execution quality therefore increases both in the B2B spread $S$ and concavity parameter $\nabla$. Equation (4) implicitly defines the concavity parameter $\nabla$ as a function of the inter-dealer half-spread $\frac{S}{2}$. A particular parameter combination $(\frac{S}{2}, \nabla)$ corresponds to optimal B2C quotes. This equilibrium schedule is graphed in Figure 3 as the B2C equilibrium schedule in a space spanned by $\frac{S}{2}$ and $\nabla$. The concavity parameter $\nabla$ monotonically increases in the B2B half-spread $\frac{S}{2}$. Intuitively, higher inter-dealer spreads render inventory imbalances more costly as rebalancing occurs at less favorable transaction prices. An increase in $\nabla$ affects the optimal quotes differently, according to a dealer’s inventory state. The optimal B2C quotes $a(1)$ and $b(-1)$ become more favorable as dealers seek to substitute B2C trades for more costly B2B trades, while B2C quotes under balanced inventories $a(0)$ and $b(0)$ deteriorate.

We can therefore conclude that a larger B2B spread $S$ deteriorates B2C quote quality at the inventory constraints. It also magnifies the degree of inventory shading (captured by the parameter $\nabla$) in an effort to avoid costly B2B rebalancing. The conditions $S < \frac{2}{\epsilon} - 4\epsilon$ and $\epsilon < \tau$ guarantee that the optimal B2C prices fall on the support $[\pm \epsilon, \frac{1}{d} \pm \epsilon]$ of the reservation price distribution in $t + 1$. The next section develops the equilibrium condition for the inter-dealer market.

### 4.4 Competitive B2B Spreads

A competitive market structure for inter-dealer quotes implies that identical dealers with identical inventory levels compete away all rents in the B2B segment. Inter-dealer competition makes dealers
indifferent as to whether their limit order is executed or not.\(^7\) Hence, inter-dealer transactions do not modify the value functions of the dealers. The first-order conditions developed in proposition 2 remain valid, even if we allow dealers to engage in B2B liquidity supply through an electronic limit order market.

Dealers with extreme inventories have a value function that is lower by \(\nabla > 0\). Dealers with a negative inventory position of \(-1\) gain \(\nabla\) by increasing their inventory level to zero and dealers with a positive inventory position \(\text{also}\) gain \(\nabla\) by decreasing their inventory to zero. Hence, dealers with a short inventory position will provide the most competitive inter-dealer bid \(B\) while dealers with a positive inventory submit the most competitive inter-dealer ask \(A\). The competitive spread is therefore determined by the dealers with extreme positions who make a gross gain \(\nabla\) by moving to a zero inventory position. A larger concavity of the dealer value function with respect to inventory imbalances should (ceteris paribus) reduce the inter-dealer spread.

But competitive B2B limit order submission also accounts for the adverse selection risk. Limit order submission in the inter-dealer market also amounts to writing a trading option that other dealers can execute. In particular, we assume that a dealer with an inventory position deteriorating from \(-1\) to \(-2\) following a customer buy order immediately needs to rebalance to \(-1\) by resorting to a market buy order in the inter-dealer market. Under assumption 1, the distribution of the customer reservation prices is assumed to move up or down by \(\epsilon\). For example, a rise in the mid-price \((\Delta x_{t+1} = \epsilon > 0)\) increases customer demand at the ask. The area of the reservation price distribution that leads to the customer acceptance of a dealer quote at the ask increases by \(\epsilon d\) because the reservation price distribution is uniform. This probability change is multiplied by the probability \(q\) of customer arrival to produce an upward demand shift of \(\epsilon q d\). Similarly, sales at the bid to a dealer with inventory \(1\) fall by the same amount. Analogous remarks can be made for a fall in the mid-price process.

The customer demand increase at the ask price, \(a(-1)\), for a dealer with inventory \(-1\) spills over into the B2B market. Similarly, the customer sales decrease at the bid, \(b(1)\), faced by a dealer with inventory \(1\) is also passed on to the B2B market. The B2B market order flow is therefore correlated with \(\Delta x_{t+1}\). Hence, the limit order submitting dealer in the B2B market is exposed to an adverse selection problem. She faces a systematically higher execution probability at the ask price \(A\) if the customer moves toward a higher valuation, and a lower execution probability for limit orders at the bid price \(B\). The following proposition characterizes the expected adverse selection loss and the competitive

\(^7\)For the competitive setting to prevail, we assume that there are always (at least) two dealers with extreme positive or negative inventory positions, respectively. Bertrand competition on each side of the market then implies a competitive B2B spread.
B2B half-spread $S$.

**Proposition 3 : Competitive B2B Quotes**

The expected adverse selection loss due to executed limit order at both ask and bid is given by

$$L = L^A = L^B = \frac{2\tau^2}{\frac{1}{\varphi} - \frac{S}{\tau}} > 0.8$$

Under quote competition in the B2B market, the competitive ask and bid prices are given by

$$A = \max(L - \nabla + \tau, 0) = \frac{S}{\varphi},$$

$$B = \min(-L + \nabla - \tau, 0) = -\frac{S}{\varphi},$$

respectively, where $\tau$ represents the order processing costs of the liquidity provider and $\nabla$ denotes the concavity parameter of the dealers’ value function.

Proof: See online Technical Appendix C on the authors’ webpage.

The only occasion in which a market order is submitted is when the dealer gets pushed over the boundary from +1 to +2 or from -1 to -2. In the case of an excessive long position (+2), the dealer submits a sell market order while an excessive short position (-2) leads to a buy market order. A dealer that is in the +1 position is showing a limit sell order at the best in the book. Optimal B2B ask pricing ensures that the dealer is indifferent between remaining in that position or being picked off and being brought to a zero inventory status. That is why she would never submit a sell market order. Of course, a dealer in the +1 position would never submit a buy market order because this would unbalance her inventory.

An interesting feature of Proposition 3 is that the expected adverse selection loss of an executed limit order does not depend on the distribution of inventories across the dealers. This seems counter-intuitive at first. A larger number of limit order submitting traders, for example, reduces the likelihood of execution for any given limit order. However, what matters for the adverse selection loss of executed trades is not the likelihood of execution itself, but the probability of adverse mid-price movement conditional on execution. The latter is not contingent on the distribution of dealers across the inventory states.

8 Recall that the properties of the uniform distribution require that the denominator be positive.
Not surprisingly, the (adverse selection) loss function $L$ is increasing in the variance $\sigma^2$ of the market process $x_t$. It is also increasing in the density $d$ of reservation prices, because the more concentrated this distribution becomes, the greater the shift in demand induced by any given price change. Finally, the expected adverse selection loss is increasing in the inter-dealer spread. Note that dealers adjust their B2C quotes $a(-1)$ and $b(1)$ to a widening B2B spread $S$. If B2C execution occurs nevertheless, then it is highly correlated with the directional change $\Delta x_t$ of the reservation price distribution, which implies a high adverse selection risk for the liquidity suppliers in the B2B segment. Hence, adverse selection risk in the B2B market endogenously increases in the B2B spread through inventory shading in the B2C market. This feedback effect can generate market breakdown as highlighted in the introduction: A higher $S$ implies higher rebalancing costs and hence more price shading in the B2C market, which in turn conditions B2C execution on larger shocks to the reservation price distribution. B2B rebalancing then occurs for a more informative customer order flow and the B2B spread $S$ needs to increase further to reflect the higher adverse selection risk.

The equilibrium condition expressed in the second part of proposition 3 is straightforward. A dealer with a positive inventory submits a sell limit order at the B2B ask with price $A$. Her expected adverse selection loss conditional on execution is $L$, but she gains $\nabla$ by moving to a zero inventory if execution occurs. Under the competitive market assumption 2, her expected conditional profit is zero, hence $A + \nabla - L - \tau = 0$, where $\tau$ represents the order processing costs. An analogous remark applies at the bid price $B$. We also note that for the B2B quotes given by equation (5), dealers in inventory states $s = \pm 1$ do not find it optimal to submit market orders, as the cost $\frac{S}{2}$ exceeds their benefit $\nabla$ of rebalancing. Only dealers who run against the inventory limits at $\pm 2$ place market orders.

Proposition 3 shows that the B2B spread is given by the difference between the adverse selection loss $L$ and the benefit of moving to a zero inventory. The inter-dealer quote spread is therefore negatively related to the benefit of moving to a zero inventory position and positively to the adverse selection loss of quote submission. A higher shadow cost $\nabla$ of holding inventory imbalances therefore implies more competitive limit order submission. Very narrow B2B spreads are therefore a reflection not only of low adverse selection risk, but also of costly inventory constraints.

As with the B2C locus, we can graph the B2B locus in the $(\frac{S}{2}, \nabla)$ space. It is the parabola illustrated in Figure 3 with the label B2B. Its intercept and turning point are derived in the online Technical Appendix D.

In equilibrium, the ask price in the B2B market is the competitive price quote by a dealer on a $+1$ position who in a transaction earns his reservation price for getting back to a zero inventory (price
shade) but pays the order-processing cost, the adverse selection cost, and earns the half spread. The parabolic shape is driven by $\frac{S}{2}$ appearing in both the adverse selection cost and the half spread. For small $\frac{S}{2}$, the spread earned is the dominant part and thus drives the negative relationship. For high $\frac{S}{2}$, the adverse selection is the largest part and thus drives the positive relationship. Dealers in the B2B market have to charge larger spreads they realize they will attract the most ‘toxic’ flow from the B2C market. This positive relationship between $S$ and $\nabla$ for high adverse selection risk is depicted by the right branch of the parabola labeled B2B in Figure 3.

4.5 Existence and Stability of the Equilibrium

The previous sections derive separately the equilibrium relationship for the B2B and B2C markets in the $(\frac{S}{2}, \nabla)$ space. It is shown how the optimal quotes in the B2C market depend on the spread $S$ in the B2B market because of rebalancing costs. Inversely, the equilibrium spread in the B2B market depends on the concavity parameter $\nabla$ of the value function (and hence the maximum benefit of limit order submission) as well as on the degree of inventory shading which determines the degree of adverse selection of B2B market orders. This market interdependence requires that we solve the model for the joint equilibrium in both markets. The joint equilibrium solution is illustrated in Figure 3 as the intersection of the B2B and B2C graphs. Figure 3 highlights that there could be up to two equilibria. We label the equilibrium where both $\frac{S}{2}$ and $\nabla$ are high as $Z_U$, in contrast to the equilibrium $Z_L$ with low values of $\frac{S}{2}$ and $\nabla$. It is straightforward to identify $Z_U$ as the unstable equilibrium. Assume two dealers with opposite inventory positions deviate from equilibrium $Z_U$ to $Z_L$ by quoting the much narrower inter-dealer spread $S_L$. Since the effective inter-dealer spread is determined by the most competitive quote, their quoted spread $S_L$ becomes the new reference point for the customer segment of the market. Hence, all customer quotes in the B2C market also adjust to the new equilibrium $Z_L$, whereby the previous equilibrium is identified as unstable. Note that the equilibrium $Z_L$ cannot be destabilized by the reverse process of two dealers quoting higher spreads. Their B2B quotes would stand no chance of being executed. Hence these non-competitive quotes are irrelevant and cannot trigger any adjustment in the B2C segment of the market. We can therefore conclude that $Z_L$ is the only stable equilibrium and discard $Z_U$.

Proposition 4: Equilibrium Existence and Stability

Under assumptions (1) to (3) and market variance $\sigma^2$ below some threshold $\sigma^2$, there exists a single stable equilibrium pair $(\frac{S}{2}, \nabla)$ for the B2B spread $S$ and the convexity of the
dealer value function $\nabla$, such that (i) dealers make optimal customer quotes as stated in proposition 2, and (ii) these quotes imply a value function with convexity $\nabla$ so that $S$ is the competitive B2B spread as stated in proposition 3.

Proof: See online Technical Appendix D.

The uniqueness of the stable equilibrium $Z_L$ allows us to undertake comparative statics with respect to the price variance $\epsilon^2$. Note that the price volatility is directly tied to the information asymmetry between customer and dealer and the degree of adverse selection under quote provision. The axis intercepts in Figure 3 show that a variance increase (higher $\epsilon^2$) pushes the B2B locus upwards and the B2C locus to the right. The B2B spread unambiguously increases. The same is true for an increase in the order processing costs $\tau$, which also shifts the B2B schedule upwards. Again, the inter-dealer spread $S$ increases as the higher cost of liquidity provision in the B2B market is incorporated into the inter-dealer spread. But we can also highlight a small increase in order processing costs $\tau$ – for example an exogenous security transaction tax – can induce a disproportionately larger increase in the B2B spread $S$. The reason here is again that higher rebalancing costs accentuate inventory shading in the B2C market and therefore increase the adverse selection risk of market orders in the B2B segment.

It is also instructive to consider two boundary cases. First, for zero volatility, the B2C schedule passes through the origin, while the intercept for the B2B curve is at the level $\tau$. In the absence of any adverse selection, the inter-dealer spread reaches its minimum at a level that is less than the order processing cost because the dealer is still partly compensated by an option value of inventory holding $\nabla$, which remains positive. For zero order processing costs ($\tau = 0$), the competitive inter-dealer spread becomes zero. Second, consider a high level of price variance given by $\epsilon^2 = \frac{1}{16\sigma^2}$. At this level of variance the B2C equilibrium schedule degenerates to a single point $(\frac{1}{\sigma},0)$ without any possible intersection with the B2B locus. We conclude that at very high levels of volatility, the adverse selection effect does not allow for a market equilibrium. The market equilibrium can only exist for a volatility of the process $x_t$ below a critical threshold so that the B2B and B2C schedules still intersect.

The derivation of the joint equilibrium implicitly assumes that there are, at any period, dealers with inventory positions 1 and $-1$, who maintain the inside B2B spread $S$. This assumption is generally fulfilled in a large market with many dealers. However, for dealership markets with only a few dealers this might be more problematic. In that case the positive probability of having to rebalance at a wider inter-dealer spread has to be incorporated into the model.
An interesting regulatory issue concerns the role of order processing costs $\tau$ for market quality. A central counterparty (CCP) with more market power is likely to charge a higher fee for B2B transactions? Similarly, any security transaction tax (STT) on B2B trades should have the very same effect of increasing $\tau$. In both cases the B2B schedule shifts upwards so that its intersection $Z_L$ with the B2C schedule occurs at a higher B2B spread $S$ and for a higher convexity parameter $\nabla$. More inventory convexity of the dealer value function increases the dispersion of B2C quotes. Moreover, the upward shift of the B2B line reduces the critical level of market volatility at which market breakdown occurs. We conclude that both more market power of the CCP or a SST generally reduce market quality and market stability.

A remedy to the market destabilizing effect of higher order processing fees is to make such fees or taxes contingent on market volatility. The optimal fee charged by the market operator should become zero or even negative when price volatility is high. This conclusion is the exact opposite of previous policy recommendations like the "Spahn tax" which propose taxation only under high levels of market volatility.

A limitation of our analysis is that dealer are risk neutral and their trading limits are exogenous; hence dealers’ trading limits are assumed to be volatility invariant. In a high volatility market, dealers might face reduced trading limits if their principles exercise active risk control. Similarly, any external change in funding liquidity for the dealer operation may also reduce inventory limits. Such additional channels for market breakdown are outside the scope of our analysis.

5 Welfare Aspects of the Dealer Structure

Dealer intermediation allows for intertemporal trades between the non-synchronous trading needs of clients; thus it enables trades that otherwise would not take place. On the other hand, dealers earn rents from their monopolistic client relationship which can increase the clients’ transaction costs. This raises the question of net welfare gain of the dual market structure against alternative trading arrangements. Under what conditions is the dual market structure beneficial to the customer with their exogenous trading needs? A natural benchmark consists of a centralized spot trading venue which clears all executable synchronous trading desires of the clients. As we consider only the aggregate trading surplus from all transactions, we can assume without loss of generality that these feasible spot transactions occur at the mid-price $x_t$. If two clients with an expected buy and sell reservation price of $x_t + \frac{1}{2d}$ and $x_t - \frac{1}{2d}$, respectively, arrive simultaneously at the spot trading venue, then a total transaction surplus of $\frac{1}{d}$ is split between both counterparties. However, if only one client is available
on either side, no transaction occurs in the absence of a dealer. Unlike the dual market structure, the
pure spot trading venue therefore requires a double coincidence of trading needs on the time line in
order to generate a trading surplus.

We can derive the overall customer rents of the spot trading venue. As for the B2C market before,
we assume that there are $N$ potential customers on both sides of the market each characterized by a
binomial process $y(i)$ with a constant probability of $q$ for his readiness to trade in time interval $t$. Total
number of spot transaction $Tr$ follows as the minimum of the $Y^A$ and $Y^B$ clients with synchronous
trading needs at the ask and bid side respectively. Formally,

$$Tr = \min(Y^A, Y^B)$$

with

$$Y^A = \sum_{i=1}^{N} y(i), \quad Y^B = \sum_{i=1}^{N} y(i)$$

Some straightforward, but tedious calculations show that the expected trading volume has an approx-
imate solution

$$E(Tr) \approx \frac{1}{2} Nq - \frac{1}{\sqrt{2\pi}} \sqrt{Nq(1-q)}.$$

The expected trading volume increases in the expected arrival of clients at each side of the market
$\mu_Y = Nq$, but decreasing in its standard deviation $\sigma_Y = \sqrt{Nq(1-q)}$. The latter being high increases
the potential for a substantial bid-ask side mismatch resulting in a reduced number of transactions.

Consumer surplus generated by spot trading follows simply as

$$W^{\text{Spot}} = \frac{1}{d} E(Tr)$$

We can contrast this market benchmark for client welfare with the corresponding client surplus
generated by the dealer market structure. Some simplifying assumptions allow us to obtain closed
form solution again. If we assume that transaction probabilities are approximately similar for all three
inventory states, we can characterize the average monopolistic dealer price markup as $\frac{1}{2d} + \frac{S}{12}$ and
obtain for the execution probability

$$P[y(i) = 1] = q \left( \frac{1}{2} - \frac{S}{12}d \right),$$

where $S$ denotes the equilibrium spread in the inter-dealer market and $Sd < 2$. The total expected

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9 See online Technical Appendix E
client surplus in each trading interval follows as\textsuperscript{10}

\[ W^{\text{Dealer}} = N P[y(i) = 1] \frac{1}{2} \left( \frac{1}{2d} - \frac{S}{12} \right) = \frac{qN}{8d} \left[ 1 - \frac{Sd}{6} \right]^2. \]

Here, the consumer surplus does not decrease in the variance of the customer arrival at each side of the market. Instead it decreases in the cost of dealer rebalancing in the inter-dealer market captured by the inter-dealer market spread \( S \). A comparison of customer surplus under the two market structures then yields the following proposition:

**Proposition 5: Welfare Gains from a Dealer Intermediation**

A market structure based on dealer intermediation yield higher consumer surplus than a pure spot trading venue if the expected number \( \mu_Y = Nq \) of clients with trading needs in each period is small such that

\[ \mu_Y < \frac{2(1-q)}{\pi} \left[ \frac{(144)^2}{d^2S^2 - 12dS - 108} \right]. \]

Proof: See online Technical Appendix E.

Generally, the dealership structure dominates the spot trading venue if the expected rate \( \mu_Y = Nq \) of clients arrival is low on both sides of the market. This increase the likelihood for a non-coincidence of trading desires in each interval and renders a welfare advantage to the dual market structure in spite of the rent dissipation through monopolistic pricing in the B2C segment. Intuitively, dealership structure should therefore flourish in “thin” markets with a high demand of trade intermediacy. We also note that a higher inter-dealer spread \( S \) and a higher dispersion \( d \) of customer reservation prices reduce quality of dealer quotes and therefore reduce the relative attractiveness of the dealer structure. Moreover, the dealership structure is susceptible to market breakdown as already highlighted in the previous section.

### 6 Incorporating Dealer Competition

#### 6.1 Sophisticated Customer

The model so far assumed maximal (monopolistic) market power of dealers towards all their clients. The following section relaxes this assumption. We now assume that a customer share \( \lambda \) is highly

\textsuperscript{10}This calculation does not include the adverse selection gain of the customer at the cost of the dealer. We therefore consider customer welfare net of adverse selection losses of dealers.
sophisticated and able to make a reverse offers to the dealer which are just a small \( \varepsilon > 0 \) below a dealers reservation price of the dealers with an extreme inventory state, that is, at reservation prices \( a(1) + \varepsilon \) and \( b(-1) - \varepsilon \) on the ask and bid side, respectively. These customers will therefore obtain the best possible deals and extract all the rents (except \( \varepsilon \)) for themselves.

**Assumption 4: Different Customer Types**

A share \( 0 < \lambda < 1 \) of sophisticated customers engages in reverse offers to the dealer with an \( \varepsilon \) price improvement over his reservation prices \( a(1) \) and \( b(-1) \) at the ask and bid side, respectively. All other customers trade as before.

An increasing share of sophisticated customers limits the overall rents a dealer can extract from his customer pool. We can also think of the sophisticated customers as those who pick dealers according to the best deal available in the entire B2C market. Their presence is therefore like a reduced form assumption about inter-dealer competition.

We highlight that this model extension is relatively tractable because additional transaction at dealer reservation prices only alter the transition probabilities between inventory states in the matrix \( M \). While this changes the value function and its convexity parameter \( \nabla \), this does not alter—except indirectly through \( \nabla \)—the first-order conditions in proposition 2. Moreover, the introduction of the sophisticated traders does not affect the B2B equilibrium schedule in Figure 3. Only the B2C schedule undergoes a shift as explained in the following section.

### 6.2 Equilibrium Effects of Dealer Competition

Sophisticated customers engage in B2C transaction at the dealer’s reservation price, which means that there is no added surplus to be gained for the trader. However, the dealer’s inventory state will change for an ask transaction from 1 to 0 and for a bid transaction from \(-1\) to 0. If we account both for the smaller share \( 1 - \lambda \) of ordinary customers altering inventory states and for the increase in the transition probabilities \( p_{10} \) and \( p_{-10} \) due to sophisticated customers, we can rewrite the new transition matrix \( M_\lambda \) as a sum of the old matrix \( M \) and its change:

\[
M_\lambda = M + \begin{bmatrix}
q\lambda \{1 - a(1)d\} - q\lambda & -q\lambda \{1 - a(1)d\} + q\lambda & 0 \\
-q\lambda \{1 + b(0) d\} & q\lambda \{1 + b(0) d\} + q\lambda \{1 - a(0)d\} & -q\lambda \{1 - a(0)d\} \\
0 & -q\lambda \{1 + b(-1) d\} + q\lambda & q\lambda \{1 + b(-1) d\} - q\lambda
\end{bmatrix}
\]
Sophisticated traders accelerate the rebalancing of extreme inventory position to a zero inventory state, but they simultaneously reduce the average rent associated with such rebalancing. We highlight that this should be the general effect of dealer competition, because deal shopping customers will tend to find the best offers from dealers with extreme inventory states and at the same time a reduction in the dealer’s market power (vis a vis) such sophisticated customer will tend to depress the average dealer rent per transaction.

The new value function is implicitly defined by the condition

$$[I - \beta M_\lambda] V(s) - \Lambda_0 - \Lambda_\lambda - \Phi = 0$$

where

$$\Lambda_\lambda = -\beta q \lambda \begin{bmatrix} \nabla \\ 0 \\ \nabla \end{bmatrix}$$

denotes loss in dealer rents relative to the benchmark model. Solving this matrix equation in terms of the inter-dealer spread $S$ and the convexity parameter $\nabla$ yields the new B2C equilibrium schedule. The following proposition summarize its behavior in terms of changes in the parameter $\lambda$.

**Proposition 6: Market Equilibrium with Sophisticated Customers**

A larger share $\lambda$ of sophisticated customers shifts the B2C schedule downwards with the following implications:

1. the inter-dealer spreads $S$ monotonically increases;
2. the convexity parameter $\nabla$ decreases (increases) at low (high) volatility;
3. B2C prices become less (more) dispersed for ordinary clients under low (high) volatility;
4. market breakdown occurs at lower volatility (and less adverse selection).

Proof: See online Technical Appendix E.

The intuition for these results is relatively simple. Sophisticated customers provide dealers with an additional rebalancing opportunity captured by the relative increase of the off-diagonal elements $(1, 2)$ and $(3, 2)$ in the transition matrix $M_\lambda$. This increases the likelihood of a balanced inventory state and makes the dealers less likely to resort to costly rebalancing in the inter-dealer market. For any given rebalancing cost given by the inter-dealer spread $S$, the convexity parameter $\nabla$ should therefore take on
a lower value. But this exactly corresponds to a downward shift in the B2C schedule. Implications (1) to (4) then directly follow from the graphical analysis provided in Figure 4 for a static B2B schedule. Under a downward B2C shift, the stable equilibrium point $Z_L$ moves to the right, which correspond to a higher inter-dealer market spread $S$. If the stable equilibrium $Z_L$ is situated on the left (right) branch of the B2B schedule, then the downward shift of the B2C schedule decreases (increases) the convexity parameter $\nabla$; implying less (more) price discrimination across inventory states and therefore more B2C price dispersion among non-sophisticated customers. Finally, a flatter B2C schedule make it more likely that no intersection with the B2B schedule occurs; hence the higher market fragility of the dual market structure under an increased share of sophisticated rent-capturing customers.

7 Evidence from the European Sovereign Bond Market

The market structure in the European sovereign bond market corresponds to the two tier framework captured in our model of dealer intermediation. The following empirical analysis focus on three key predictions of our model; namely (i) a large dispersion of B2C spreads due to inventory contingent dealer pricing; (ii) an increase of both the B2B spread and the B2C price dispersion in bond maturity as a reflection of adverse selection risk; and (iii) evidence that the dealers aggregate inventory situation (as proxied by B2B limit order imbalances) directly correlates with the quality of B2C ask and bid side transactions with the opposite sign.

7.1 Market Overview

The market participants in the European bond market can be grouped into primary dealers, other dealers, and customers. Customers are typically other financial institutions, like smaller banks or investment funds. Dealers have access to electronic inter-dealer (B2B) platforms, of which the most important is MTS. Its largest market share is in Italy, where it has close to 100 percent. In other countries MTS has a lower market share but overall, approximately half of all inter-dealer trades are transacted through MTS. Trading in the MTS inter-dealer platform is similar in operation to any electronic limit order book market.

At the time of our study, B2C transactions took place both over-the-counter and on various trading platforms. The Eurex platform had not long been established and did not have a large share of the market. Also, Bloomberg’s BBT platform was mostly a repository for limit orders and expressions of interest in awkwardly sized or very small orders. TradeWeb and BondVision customers

\[\text{footnote}^{11}\text{For more institutional background, see also Dunne et al. (2006, 2007).}\]
were able to submit simultaneously ‘requests-for-quotes’ (RFQs) from a small number of dealers who could potentially supply instant responses that could be accepted electronically. Though TradeWeb has a slightly larger market share than BondVision, the latter is operated by MTS in parallel with its B2B platform and thus it was easier to compile consistent and accurate time-stamped data from the two segments by using BondVision data. The BondVision platform represents a significant proportion of B2C electronic requests for quote (RFQ) trading, particularly for Italian issues. Given the strong market position of MTS in the Italian B2C segment, it is natural to focus much of our empirical analysis on Italian bonds.

7.2 MTS and BondVision Data

We explore a new data set that combines both inter-dealer (B2B) and dealer-customer data (B2C). The data cover the last three quarters of 2005. Events are reliably time stamped and trade initiation is electronically signed in both markets. In the case of the B2B market we obtained observations about the state of the limit order book at a per second frequency and we were also provided with transaction data on an event basis. Our empirical analysis involves a comparison of the transactions with customers on the BondVision platform with the prevailing quotes made between dealers on the B2B platform at the exact time of the customer requests for quotes.

Over the data period 72 (268) different Italian (non-Italian) bonds were traded on both MTS and BondVision. Our sample consists of 105,469 (83,313) Italian (non-Italian) bond B2B trades and 28,245 (17,259) Italian (non-Italian) bond B2C trades. The majority of trades in each case concern so-called benchmark bonds. The ‘benchmark’ attribute that we employ is defined by MTS and refers to bonds for which primary dealers have liquidity provision obligations. We also group the bonds into three different maturity groups. Short-medium bonds have a maturity of 1.5 to 7.5 years, long bonds of 7.5 to 13.5 years and very long bonds feature maturities beyond 13.5 years.

The unique feature of our data is that they combine inter-dealer and dealer-customer price data. It is therefore straightforward to assess the competitiveness of the B2C segment by comparing the B2C trades to the best B2B quote at the same side of the market. We distinguish B2C trades that occur at the ask and compare them to the best B2B ask price prevailing at the same moment in time. Similarly, B2C trades at the bid side of the market are compared to the best available contemporaneous B2B

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12 Summary statistics are available on request.
bid price. We refer to this price difference as cross-market spread, defined as

\[
\text{Cross-Market Spread (Ask)} = \text{Best B2B Ask Price} - \text{B2C Ask Price} \\
\text{Cross-Market Spread (Bid)} = \text{B2C Bid Price} - \text{Best B2B Bid Price}.
\]

We present three strands of evidence. Firstly we provide a non-parametric analysis of cross-market spreads under different categories of bond liquidity. Secondly, we provide a similar analysis across different bond maturities. Finally, we carry out a full regression analysis to test the model implications for market volatility.

7.3 Market Quality by Bond Liquidity

How favorable are B2C transaction prices in BondVision relative to the best B2B quote on the same side of the market in the MTS inter-dealer platform? Table 1 addresses this question for the total sample of 340 bonds. It reports the cross-market spread for ask side trades and (separately) bid side trades for bonds in the four liquidity groups. The four liquidity categories are a two-by-two classification by Italian/non-Italian and benchmark/non-benchmark bonds. The cross-market spreads for each liquidity category are grouped into quartiles, where Q(1) denotes the 25 percent lowest (best) cross-market spreads and Q(4) represents the 25 percent highest (worst) spreads from the customer perspective. We report the quartile mean as well as the overall mean.

The insight from Table 1 concerns both the overall quality of B2C trades as well as their large dispersion relative to the best B2B quotes. First, the average B2C trade quality appears high. The mean cross-market spread is positive for Italian and non-Italian bonds, for benchmark and non-benchmark bonds and on both bid and ask side transactions. Even the mean of the 25 percent worst B2C transactions on the ask side shows a slightly positive cross-market spread. Their execution quality is therefore too favourable relative to the negative cross-market spread $\frac{1}{2}S - a(-1) < 0$ predicted by the model for the worst B2C transactions. On the bid side, B2C trades are slightly less favourable. The 25 percent worst trades show an average transaction price outside the B2B spread in line with the model prediction. The cross-market spread is somewhat smaller for Italian benchmark bonds compared to the other three categories. But the overall finding is similar across all four groups. B2C transactions occur on average at or inside the B2B spread. Second, the dispersion of the cross-market spread is substantial. It ranges from an average of 4.80 (4.75) cents for the 25 percent best B2C ask (bid) side trades to 0.24 (−0.38) cents for the 25 worst B2C ask (bid) side trades. This is large relative to an average inter-dealer (B2B) spread of approximately 4.31 cents. It is our contention that such quality dispersion of B2C trades can be explained by our model of inventory contingent dealer quotes.
The right-hand side of panels A and B report the distribution of B2B spreads recorded at the time when B2C trades occur. On the ask side, the average B2B half-spread is 1.98 cents (≈ 1.98 basis points) and can be compared to the average cross-market spread of 1.99 cents (≈ 1.99 basis points). This implies that ask side B2C trades occur on average at the midpoint of the B2B spread. On the bid side, B2C trades are slightly less favorable, but still extremely ‘low cost.’ B2C trades are centered around a price level between the B2B midprice and the best B2B bid price, as the comparison between the average cross-market spread of 1.49 cents and the B2B half-spread of 2.33 cents reveals.

### 7.4 Market Quality by Bond Maturity

One explanation for the large dispersion of B2C trade quality is dealer price discrimination by customer type. Less sophisticated customers may for example obtain systematically worse B2C quotes. Under this alternative hypothesis, the B2C price dispersion should be unrelated to the adverse selection risk and inventory constraints of the dealers. While we cannot sort cross-market spreads by customer type (for lack of customer information), we can reproduce Table 1 sorted by bond maturity. Long-run bonds have a higher duration and their larger interest rate sensitivity implies that price volatility and adverse selection risk are considerably larger than for bond of short maturity. According to our model of inventory-based price differentiation, the B2C price dispersion increases in midprice volatility and therefore also in bond maturity.

Table 2 presents cross-market spreads for 171 benchmark bonds (Italian and non-Italian) classified by three maturity groups. The mean B2B ask (bid) side half spread in Panel A (Panel B) increases from 1.01 (0.99) cents to 5.38 (5.12) cents when comparing very long bonds to short-medium bonds. This fivefold increase highlights the strong sensitivity of the B2B to adverse selection risk. By contrast, the mean cross-market spread shown on the right side of Table 2 increases less on both the ask and bid side, which implies higher relative transaction quality for B2C transaction as monopolistic dealers absorb some of the adverse selection risk in the B2C segment. The dispersion of the cross-market spread between the 25% best and worst B2C trades is 1.75 (1.48) cents on the ask (bid) side for short and medium maturities and increases to 9.59 (9.21) cents on the ask (bid) side for the very long maturities. The B2C price dispersion therefore increases by more than a factor of five for bonds of high duration. This feature of the data cannot be accounted for by customer based price discrimination since customers of very different financial sophistication are likely to request both long and short maturity bonds. Overall, the data sort on bond maturity suggests that B2C trade quality dispersion is driven by a dealer’s inventory management costs (i.e. the cost of rebalancing in the B2B market)
rather than a pure customer-based price discrimination.

### 7.5 Market Quality by Inventory Imbalances and Market Volatility

It is clear from Figure 4 that an implication of the model is that higher adverse selection, as measured by volatility, implies that the quality of the average B2C spread should improve relative to the B2B spread. So the average cross-market spread should decrease in volatility on both the ask and bid sides of the market. The other important feature of the model is that the B2C quotes depend on the inventory state of the dealer. Unfortunately, such inventory data are not directly available. However, inventory imbalances also induce dealers to submit the most competitive B2B quotes. The relative depth of the best B2B quotes indicate the distribution of inventory imbalances within the dealer population. Therefore we measure aggregate inventory imbalances as

\[
Imb = \frac{Q(\text{Ask}) - Q(\text{Bid})}{Q(\text{Bid}) + Q(\text{Ask})}
\]

where \(Q(.)\) denotes the limit order book liquidity at the best ask or bid, respectively.

Figure 4, panel A plots the average cross-market spread \(A - a\) on the ask side as a function of the inventory imbalance and the volatility. The corresponding cross-market spread \(b - B\) on the bid side is featured in panel B. As before, higher volatility increases this spread because of the higher volatility sensitivity of the B2B spread \(S\). Moreover, Figure 4 also reveals the dependence of the cross-market spread on the inventory imbalance. A more positive aggregate inventory imbalance, namely more dealers in state \(s = 1\) relative to \(s = -1\), comes with a lower average ask quote \(\bar{a}\) and therefore a higher cross-market spread on the ask side. On the bid side, the cross-market spread decreases in the imbalance statistic, as depicted in panel B. Intuitively, a positive imbalance comes with a tilt of the probability distribution of dealer states toward \(s = 1\). This implies that relatively more dealers quote B2C prices \(a(1)\) or \(b(1)\) relative to \(a(-1)\) or \(b(-1)\). Hence the average cross-market spread improves on the ask side and deteriorates on the bid side. The previous regression is now extended as follows:

\[
\text{Cross-Market Spread (Ask)} = A - a = \mu_{a0} + \mu_{av} \times Vol + \mu_{aI} \times Imb + \eta_a
\]
\[
\text{Cross-Market Spread (Bid)} = b - B = \mu_{b0} + \mu_{bv} \times Vol + \mu_{bI} \times Imb + \eta_b
\]

where \(\eta_a\) and \(\eta_b\) are i.i.d. processes, \(\mu_{a0}, \mu_{av}, \mu_{aI}, \mu_{b0}, \mu_{bv}\) and \(\mu_{bI}\) are parameters. The null hypotheses are that \(\mu_{av} = \mu_{bv} > 0\) and \(\mu_{aI} = -\mu_{bI} > 0\).

A potential problem with this regression is simultaneity bias. Price outliers in the inter-dealer market tend to influence both the B2B half-spread and the volatility measurement in the same period. To avoid this simultaneity bias, we use again an instrumental variable approach based on lagged
rather than contemporaneous volatility. We also include fixed effects for each bond to control for heterogeneity across bonds.

In Table 3, columns (10) and (12) present the regression results for the cross-market spread. Panel A reports the regression results for the ask side and panel B for the bid side of the market. The analysis here focuses on the Italian bonds because of the high market coverage of our B2C data for this segment. In each case we run a regression for the full sample of all 13 liquid Italian government bonds and the subsample of six most liquid long-dated Italian government bonds. The six long-dated bonds form a particularly homogenous subsample in terms of coupon rates, maturity, and liquidity characteristics, and at the same time represent a large share of the overall bond transactions in Italian long-dated bonds.\textsuperscript{13} The cross-market spread on the ask side is almost constant in volatility and increasing on the bid side. The increase on the bid side is statistically significant at the 1 percent level for the full sample though the significance is marginal for the subsample of long maturity bonds. For the ask side, we cannot confirm that the predicted cross-market spread increases in volatility. Hence, there is no change in the B2C ask side trade quality (relative to the best B2B quote) as volatility changes.

The results for the inventory dependence of the cross-market spread are more clear-cut. The estimation coefficients have the signs predicted under the null hypothesis and are therefore consistent with the numerical results depicted in Figure 4.\textsuperscript{14} The imbalance measure itself is statistically highly significant with t-statistics always above 7 in absolute value. For the ask side we find a positive effect on the cross-market spread and for the bid side a negative coefficient as proposed under the null.

The B2B spreads in Table 3, columns (1) to (4), show, as expected, a highly significant positive volatility dependence. The volatility dependence in the full sample is stronger on the bid side than the ask side with coefficients 0.554 and 0.277, respectively. The more positive volatility dependence for the B2B spread on the bid side may explain algebraically why we find a more positive volatility dependence for the cross-market spread on the bid side as well. The asymmetry in the spread behavior between the ask and bid side needs to be explained by forces outside the current model framework. It is reassuring that the B2B spreads do not display a pattern of statistically significant dependence on inventory imbalances. For completeness, columns (5) to (8) of Table 3 display the results of using

\textsuperscript{13}The results are also conditioned on two controls. The log of B2C transaction size controls for trade size while competition effects are controlled for by the use of separate intercepts for RFQs from a single dealer and RFQs from more than one dealer.

\textsuperscript{14}The imbalance measure is almost orthogonal to the volatility measure (their correlation is a mere .0076) and its inclusion in the regression is without consequence for the spread-volatility nexus as is clear from the odd-numbered columns.
B2C spreads as the dependant variable

Finally, we highlight that the point estimates, in absolute value, for imbalances in the cross market spread equations in columns (9) to (12) of Table 3 vary between 0.313 and 0.477: these are also economically significant. To see this, assume that inventory imbalances move over half the maximal range from $-0.5$ to $0.5$. The coefficient estimates then represent the corresponding change in the B2C price quality in cents. Such an inventory-related price change is large considering that, as Table 3 shows, the B2B half-spreads are on average only 1.40 cents on the ask side and 1.68 cents on the bid side whenever B2C trades occur. A two standard deviation increase in the imbalance variable improves ask-side B2C transactions by 0.42 basis points and deteriorates bid-side transactions by 0.30 basis points. Inventory imbalances proxied by liquidity imbalances in the B2B market therefore explain economically significant variations in B2C transaction price quality.

8 Extensions and Limitations of the Analysis

Our simple dynamic market intermediation problem of optimal B2B and B2C price setting already gives rise to a relatively rich model in the case of only three inventory states. Here we point out some possible extensions.

A first generalization is to extend the number of inventory states from 3 to $2n + 1$. Since every inventory state comes with separate first-order conditions for the B2B and B2C segment, we would have to solve $4n + 2$ equations. Instead of a single convexity parameter $\nabla$, we would have to solve for a set of $n$ value function parameters. But we do not see that this increased complexity renders any new qualitative insights into the dynamics of the intermediation problem.

A second more interesting extension consists of allowing for asymmetry of the reservation price distribution on the ask and bid side. Summary statistics in Tables 1 and 2 show somewhat more favorable cross-market spreads on the ask than on the bid side. One straightforward explanation could be that the distribution of customer reservation prices is more dense on the ask side. The model can capture this by distinguishing the ask side distribution of reservation prices by a parameter $d_a$ from the corresponding bid side parameter $d_b$ with $d_a > d_b$. This symmetry-breaking assumption implies that first order conditions on the ask and bid side are no longer mirror images and the value function is no longer symmetric in inventory imbalances. We rather obtain separate convexity parameters $\nabla_a$ and $\nabla_b$ influencing ask and bid side quotes differently. While this is still rather tractable and can capture bid- and ask-side asymmetry, we conjecture that the fundamental insights of the models are not altered.
A still more desirable extension would be the introduction of a more general form of dealer competition for customer quotes. The model extension in Section 6 provides a first parsimonious step towards modelling reduced dealer market power, but its stylized dichotomy between price taking and price setting customers is not fully satisfying. Yet, more general extensions poses fundamental challenges. Simple Bertrand price competition in a dealer duopoly already eliminates all pricing setting power for the dealers. Such a fully competitive setting would be at odds with the evidence for inventory effects. In order to moderate price competition and retain some pricing power for dealers, additional assumptions are needed. A lack of common knowledge about the state variable $x_t$, for example, could reduce the full rent dissipation under Bertrand competition. A duopoly situation involving traders with different beliefs about $x_t$ may justify deviations from fully competitive price setting. While a richer duopolistic situation can still be modelled, its equilibrium outcome would also depend on the inventory state of each of the two dealers. Random matching of trader types would require us to keep track of the entire distribution of trader types, which greatly complicates the dynamic optimization problem. It seems technically difficult to introduce a more general version of inter-dealer competition for customer quotes into our framework.

9 Conclusions

Repeated market breakdown in the European sovereign bond market during the financial crisis calls for a better understanding of adverse selection problems in a two tier market structure. The current paper develops a theoretical framework which allows for a better understanding of dealer as intermediaries between a highly competitive centralized B2B trading platform an a network of B2C relationships. We characterize the interrelationship between both market segments. Adverse selection risk passes from the client network to the B2B market, where its concentration may generate market breakdown. The principle channel is the inventory rebalancing motive of dealers, which makes the B2B spread highly sensitive to price volatility and adverse selection risk. But there is also an important reverse effect: The B2B spread determines the rebalancing costs for the dealers and therefore feeds back to the degree of inventory shading, B2C price dispersion, and the average B2C price. If the latter increases, this may further increase the adverse selection component of the client order flow, implying still higher B2B spreads. Such a feedback loop can therefore produce market breakdown.

Our analysis has important regulatory policy conclusions. Low order processing costs in the B2B market are important for the robustness of the market structure. This implies that the market power of the B2B platform provider (or CCP) should be a prime regulatory concern. We find indeed that
the B2B spread in the European sovereign bond trading platform MTS are large relative to the B2C spreads available outside the centralized market. This points to relative important order processing costs, which should make the market more fragile and susceptible to market breakdown. At the very least one would expect full public disclosure about such order processing cost —something which is not the case today. Any increase of the order processing costs due to security transaction taxes (STT) is also detrimental to market stability as shown in our analysis. The current regulatory debate about such taxes could benefit from the structural analysis provided in this paper.
References


Figure 1: Plotted is a 20 day moving average of realized intra-day volatility based on return measurement at 15 minute intervals for various ten year benchmark bonds. The dark (light) grey background shading highlights (partial) market breakdown whenever the daily trading volume falls below the 3 percent (10 percent) average trading volume from January 2007 to July 2007 prior to the European sovereign bond crisis.
Dealers learn $x_t$

Dealers set inventory-contingent customer Quotes

Shock to distribution of customer private asset Values

Customers arrive with probability $q$ and trade depending on private values

Inter-dealer trading takes place

Dealers learn $x_{t+1}$

Figure 2: Time line for trading process
Figure 3: The B2C schedule characterizes the inventory concavity parameter $\nabla$ for optimal B2C quotes under any B2B spread $S$. The B2B schedule defines the competitive B2B spread $S$ for dealers who have $\nabla$ as their inventory concavity parameter. The two intersections fulfill the equilibrium conditions in both the B2B and B2C market. Of the two equilibria, only one, $Z_L$, is stable.
Figure 4: For the ask side (panel A) and the bid side (panel B) we plot vertically the average cross-market spread as a function of volatility ($\sigma^2$) and the aggregate inventory imbalance ($Imb$). The red area marks the region for which the average B2C spread is more favorable than the B2B spread. The order processing cost parameter is chosen as $\tau = 0.5$; the probability of customer arrival is $q = 0.5$; the discount rate $\beta = 0.99$; the density of the customer price reservation distribution $d$ is set at 1.
Table 1: Cross-Market Spreads and B2B Spreads by Liquidity

We report for each quantile of the trade price distribution (i) the average B2B spread, (ii) the average B2C spread and (iii) the average of the cross-market spread for 72 Italian and 268 non-Italian European sovereign bonds of high (B=benchmark) and low (NB=non-benchmark) liquidity. Panel A reports average spreads for transactions at the ask quotes while Panel B reports spreads for bid transactions. The B2B or B2C spreads are measured relative to the mid-price $\text{MidP}$ between the best B2B ask and bid at the same moment in time when the B2B or B2C transactions occur. The cross-market spread is defined as the difference between the B2C transaction price ($a$ or $b$ for B2C ask or bid, respectively) and the prevailing best B2B price ($A$ or $B$ for B2B ask or bid, respectively). All spread measures are given in cents. At par, these amount to basis points.

### Panel A: Ask-Side Spreads

<table>
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<td>$a - \text{MidP}$</td>
<td>$A - a$</td>
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<td>Non-Italian Bonds</td>
<td>Italian Bonds</td>
<td>Non-Italian Bonds</td>
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<tr>
<td>Mean of Q(1)</td>
<td>Best</td>
<td>0.64 0.24</td>
<td>0.90 0.89</td>
<td>0.70</td>
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<td>Mean of Q(2)</td>
<td>1.00</td>
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<td>0.15 0.00</td>
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<td>Mean of Q(3)</td>
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<td>Mean of Q(4)</td>
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<td>Overall Mean</td>
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<td>1.70 1.99</td>
<td>2.26 2.11</td>
<td>1.98</td>
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### Panel B: Bid-Side Spreads

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<td>$b - B$</td>
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<td>Italian Bonds</td>
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<td>Mean of Q(1)</td>
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<td>0.76</td>
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<td>Mean of Q(2)</td>
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<td>0.45 0.39</td>
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<td>Mean of Q(3)</td>
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<td>1.69 1.50</td>
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<td>5.66</td>
<td>2.15 3.95</td>
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<tr>
<td>Overall Mean</td>
<td></td>
<td>1.82 4.00</td>
<td>2.33</td>
<td>0.84 1.38</td>
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</table>
We report for each quantile of the trade price distribution (i) the average B2B spread, (ii) the average B2C spread and (iii) the average cross-market spread for a sample of bonds grouped into three main maturity categories of 171 (Italian and non-Italian) benchmark bonds. Panel A reports average spreads for transactions at the ask quotes while Panel B reports spreads for bid transactions. The B2B or B2C spreads are measured relative to the mid-price \( \text{MidP} \) between the best B2B ask and bid at the same moment in time when the B2B or B2C transactions occur. The cross-market spread is defined as the difference between the B2C transaction price (\( a \) or \( \text{bid} \) for B2C ask or bid, respectively) and the prevailing best B2B price (\( A \) or \( \text{ask} \) for B2B ask or bid, respectively). All spread measures are given in cents. At par, these amount to basis points.

### Table 2: Cross-Market Spreads and B2B Spreads by Bond Maturity

<table>
<thead>
<tr>
<th>Quantile Means</th>
<th>Quality</th>
<th>Short-Med.</th>
<th>Long</th>
<th>Very Long</th>
<th>All</th>
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<tr>
<td>Mean of ( Q(1) )</td>
<td>Best</td>
<td>0.52</td>
<td>0.96</td>
<td>2.53</td>
<td>0.76</td>
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<tr>
<td>Mean of ( Q(2) )</td>
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<td>0.99</td>
<td>1.39</td>
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<td>1.06</td>
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<tr>
<td>Mean of ( Q(3) )</td>
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<td>Overall Mean</td>
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<td>1.01</td>
<td>1.52</td>
<td>5.38</td>
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<th>Quantile Means</th>
<th>Quality</th>
<th>Short-Med.</th>
<th>Long</th>
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<td>Mean of ( Q(1) )</td>
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<td>−1.64</td>
<td>−2.73</td>
<td>−1.53</td>
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<td>Mean of ( Q(2) )</td>
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<td>−0.37</td>
<td>−0.43</td>
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<tr>
<td>Mean of ( Q(3) )</td>
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<td>0.00</td>
<td>0.11</td>
<td>1.33</td>
<td>0.11</td>
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<tr>
<td>Mean of ( Q(4) )</td>
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<td>1.21</td>
<td>5.01</td>
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<tr>
<td>Overall Mean</td>
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<td>−0.20</td>
<td>−0.19</td>
<td>0.93</td>
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### Panel A: Ask-Side Spreads

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<th>( a - \text{MidP} )</th>
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<td>2.31</td>
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<td>Long</td>
<td>1.65</td>
<td>2.00</td>
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<td>Very Long</td>
<td>3.35</td>
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<td>1.00</td>
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<tr>
<td>All</td>
<td>4.44</td>
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### Panel B: Bid-Side Spreads

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<th>Bond Maturity</th>
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<tr>
<td>Short-Med.</td>
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<td>Very Long</td>
<td>2.36</td>
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<td>All</td>
<td>3.86</td>
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Table 3: Cross-Market Spread and B2B Spread Estimation

Reported are instrumental variable estimates of the relation between the spreads, volatility, and imbalance controlling for competition and order size where applicable. The dependent variables are (i) the B2B spread (columns 1-4), (ii) the B2C spread (columns 5-8), and (iii) the cross-market spread (columns 9-12) for the ask-side (Panel A) and the bid-side (Panel B), respectively. The explanatory variables are realized volatility and imbalance at the best quotes in the B2B market prevailing at the time of the B2C request for quotes. Volatility is measured by the log-realized volatility of the mid-price returns over one-minute intervals computed for every full hour. Imbalance ($Imb$) is measured as the difference between the B2B liquidity at the best ask and the best bid for the benchmark Italian long bond at the moment when a B2C transaction takes place in any given bond. The competition control is in the form of separate dummies for requests for quotes from one dealer and more than one dealer respectively. Order size enters as the log of B2C quantity. Results are provided for the full-sample of liquid Italian bonds and for the sub-sample containing the six very liquid long bonds. In all cases we include bond-specific fixed effects to control for spread differences across bonds. The IV regression uses a constant and volatility lagged by one hour as instruments. The t-statistics presented are based on standard errors that have been adjusted for heteroscedasticity. Spreads are expressed in cents. At par, these amount to basis points. Even-numbered regressions include the imbalance variable. The reported $R^2$ are from OLS regressions with fixed effects: they are higher for the full sample regressions because of the much larger number of bonds. The $F$ tests are for equality of the constants for competition/no-competition in regressions (5) to (12).

### Panel A: Ask-Side Spreads

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<td>0.277</td>
<td>0.408</td>
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<td>T-Stat</td>
<td>4.719</td>
<td>4.714</td>
<td>3.130</td>
</tr>
<tr>
<td>Imbalances, $Imb$</td>
<td>−0.037</td>
<td>−0.040</td>
<td>−0.265</td>
</tr>
<tr>
<td>T-Stat</td>
<td>−1.316</td>
<td>−0.820</td>
<td>−5.712</td>
</tr>
<tr>
<td>NO COMP</td>
<td>−0.023</td>
<td>−0.025</td>
<td>−0.919</td>
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<tr>
<td>T-Stat</td>
<td>−0.099</td>
<td>−0.104</td>
<td>−1.499</td>
</tr>
<tr>
<td>COMP 2+</td>
<td>0.024</td>
<td>0.252</td>
<td>0.830</td>
</tr>
<tr>
<td>T-Stat</td>
<td>0.749</td>
<td>0.769</td>
<td>0.991</td>
</tr>
<tr>
<td>Log B2C Quantity</td>
<td>−0.129</td>
<td>−0.128</td>
<td>−0.234</td>
</tr>
<tr>
<td>Obs</td>
<td>5159</td>
<td>5159</td>
<td>1561</td>
</tr>
<tr>
<td>OLS $R^2$ (no fixed effects)</td>
<td>0.833</td>
<td>0.833</td>
<td>0.436</td>
</tr>
<tr>
<td>-----------------------------</td>
<td>------------</td>
<td>------------</td>
<td>--------------------</td>
</tr>
<tr>
<td></td>
<td>Full Sample</td>
<td>Long Bonds</td>
<td>Full Sample</td>
</tr>
<tr>
<td></td>
<td>(1) (2)</td>
<td>(3) (4)</td>
<td>(5) (6) (7) (8)</td>
</tr>
<tr>
<td>Log Realized Volatility</td>
<td>0.554</td>
<td>0.590</td>
<td>0.707 0.698 0.703 0.700</td>
</tr>
<tr>
<td>Imbalances, Imb</td>
<td>0.019</td>
<td>0.074</td>
<td>0.290 0.278</td>
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<tr>
<td>T-Stat</td>
<td>0.537</td>
<td>1.763</td>
<td>5.213 3.931</td>
</tr>
<tr>
<td>NO COMP</td>
<td>-1.011</td>
<td>-1.015</td>
<td>-1.583 -1.536 3.040 3.005</td>
</tr>
<tr>
<td>COMP</td>
<td>-1.414</td>
<td>-1.406</td>
<td>2.996 2.993</td>
</tr>
<tr>
<td>T-Stat</td>
<td>-3.450</td>
<td>-3.531</td>
<td>4.787 4.776</td>
</tr>
<tr>
<td>Log B2C Quantity</td>
<td>-0.086</td>
<td>-0.082</td>
<td>-0.136 -0.135</td>
</tr>
<tr>
<td>Obs</td>
<td>4441</td>
<td>4441</td>
<td>2082 2082</td>
</tr>
<tr>
<td>OLS $R^2$ (no fixed effects)</td>
<td>0.820</td>
<td>0.432</td>
<td>0.782 0.783 0.318 0.321</td>
</tr>
<tr>
<td>$F(3)$</td>
<td>0.718</td>
<td>2.640</td>
<td>0.277 0.223</td>
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