Dealer Intermediation Between Markets

Peter Dunne*

Central Bank of Ireland

Harald Hau**

INSEAD and CEPR

Michael Moore***

Queens University, Belfast

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Abstract

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 in both markets in closed form and test the model implications for the European sovereign bond market. The model can explain (i) the high dispersion of quoted and executed customer prices due to the inventory dependence of optimal quotes, (ii) the more pronounced bid-ask spread deterioration under volatility increases for B2B relative to the B2C market, (iii) why aggregate dealer inventory imbalances coincide with asymmetric execution quality between the bid and ask side in the customer segment.

Keywords: Dealer Intermediation, Spread Determination, Adverse Selection, Market Segmentation

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*Research Department, Central Bank of Ireland, Dame Street, Dublin 2, Ireland. Telephone: (+353) 1 224 6331. E-mail: peter.dunne@centralbank.ie. Web page: www.qub-efrg.com/staff/pdunne/

**Department of Finance, Boulevard de Constance, 77305 Fontainebleau Cedex, France. Telephone: (++33) 1 6072 4484. Fax: (33)-1 6074 5500. E-mail: harald.hau@insead.edu. Web page: www.haraldhau.com

***School of Management and Economics, Queens University, Belfast, BT7 1NN, Northern Ireland, United Kingdom. Telephone: (++44) 28 9097 3208. E-mail: m.moore@qub.ac.uk. Web page: www.qub-efrg.com/staff/mmoore/

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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 in both markets in closed form and test the model implications for the European sovereign bond market. The model can explain (i) the high dispersion of quoted and executed customer prices due to the inventory dependence of optimal quotes, (ii) the more pronounced bid-ask spread deterioration under volatility increases for B2B relative to the B2C market, (iii) why aggregate dealer inventory imbalances coincide with asymmetric execution quality between the bid and ask side in the customer segment.

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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 also explore the empirical implications and test them based on new data from the European sovereign bond market. The model can explain (i) the high dispersion of quoted and executed customer prices due to the inventory dependence of optimal quotes, (ii) the more pronounced bid-ask spread deterioration under volatility increases for the B2B relative to the B2C market, (iii) why aggregate dealer inventory imbalances coincide with asymmetric execution quality between the bid and ask side in the customer segment.

The theoretical analysis focuses on the interface role of dealers between two market segments. We assume that dealers face both inventory constraints and adverse selection due to stochastically evolving private customer values. The inventory constraints imply that dealers must rebalance and submit market orders in the inter-dealer market whenever their inventory level exceeds an exogenous inventory limit. But dealers also engage in optimal price shading by adjusting their B2C quote behavior to their current inventory level. Simultaneously, dealers competitively provide B2B limit order quotes which are also inventory dependent. The competitive B2B spread fully accounts for the (endogenous) adverse selection risk in the B2B segment as well as the benefit of B2B limit order execution in terms of inventory change.

To our knowledge, the model is the first to derive the competitive B2B limit order process from the B2C market structure and determine its adverse selection component endogenously based on optimal

[1] Modelling dealer quote behavior has proven difficult in a single market so that issues of market interdependence between wholesale and customer segement 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.

dealer price shading in the B2C segment. We characterize a unique stable equilibrium in optimal B2C and B2B spreads and provide conditions for its existence. Closed from solutions allow us to understand three important channels of market interdependence in a simple and tractable manner:

1. **Rebalancing cost and B2C market quality:** B2C quote and trade quality generally depends on the dealer inventory level and on the equilibrium spread in the B2B market. A higher spread in the B2B market increases the costs of inventory rebalancing, makes the dealer's value function more convex in inventory imbalances, and magnifies the optimal B2C price shading as inventories approach the authorized limit. Hence, the rebalancing function of the B2B market implies a positive market quality externality of B2B spreads on B2C spreads. The degree of inventory shading and therefore B2C price dispersion depends on the B2B spread.

2. **Inventory constraints and B2B market quality:** The quality of a dealer's limit orders in the B2B segment depend on the inventory effects if the respective quotes are executed. The best ask (bid) side limit orders in the B2B market are submitted by those dealers with the largest positive (negative) inventory imbalances. If the dealer's value function features strong concavity in inventory imbalances, then the benefit of rebalancing through B2B limit order supply becomes large. Hence, more costly inventory constraints lower B2B spreads. Or put differently: very tight B2B spreads can reflect a strong dealer desire to rebalance through limit orders.

3. **B2C price shading and adverse selection in the B2B segment:** The optimal B2B spread must also account for the adverse selection, which itself depends on the extent of inventory shading in the B2C segment. Under high rebalancing costs in the B2B market, dealers at their inventory limit quote more unfavorable prices and quote execution at these unfavorable prices becomes more informative about shifts in the customers' private asset values. B2B market orders thus feature more adverse selection risk, so that B2B spreads increase further. This feedback effect can bring about market breakdown. Our model contributes to a better understanding of such market breakdown in a two-tier market structure.

The second part of the paper derives the empirical implications of the models and test them for the European sovereign bond market. The European sovereign bond market 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. We are able to 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.

The empirical analysis confirms the main theoretical predictions of our intermediation model. First, we find that B2C trades in the European bond market span a large range of execution quality.[2] B2C dispersion measured (for 340 different bonds) by the difference between the (average of the) 25 percent best and worst trades is 4.56 cents on the ask side and 5.13 cents on the bid side. This is large relative to an average inter-dealer (B2B) spread of approximately 4.31 cents. Such quality dispersion of B2C trades can be explained by inventory contingent dealer quotes. Second, B2C trade quality (relative to B2B inside spreads) is constant (bid side) or even improves (ask side) under increased market volatility unlike B2B spreads. Intuitively, B2B spreads are set competitively so that higher adverse selection risk associated with high volatility is fully reflected in B2B spreads. By contrast, monopolistic price mark-up in the B2C segment can absorb some of the adverse selection risk of higher market volatility. Third, aggregate inventory imbalances at the inside spread in the B2B market affect B2C quote quality on the other side of the order book. This latter aspect is predicted by our model and provides direct evidence on the role of inventory imbalances for explaining B2C quote behavior.

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.

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

[2] This occus in spite of high price transparency in the B2B segment. The interdealer segment is characterized by both pre- and post-trade transparency. There is virtually instant visibility of best quotes and recent transactions from the MTS B2B platform on Bloomberg and Reuters screens. In November 2004 the entire range of MTS data was made available in real time to a wide variety of market participants.

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.[3] 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.[4] This makes it less plausible that any price differences between the B2B and B2C transactions amount to 'trading errors'.

The following section presents the dynamic model of dealer intermediation under inventory constraints. Section 3 discusses the data from the European sovereign bond market. The empirical implication of the model are test in Section 4. Section 5 discusses extensions and limitations of our analysis followed by concluding remarks in Section 6.

2 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 a the distribution of customer reservation prices. This means that dealer customers do not behave strategically in our setup - for example by shopping for better dealers services. This aspect certainly ignores an important aspect of inter-dealer competition for clients. However, we point out that dealers are (ex ante) identical so that any permanent move to another dealer does not

[3] 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)).

[4] 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)).

provide customers with any long-run expected benefit.[5]

2.1 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

Each period a dealer faced 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 $R^a > \widehat{a}$ and sells if $R^b < \widehat{b}$, where the requested ask and bid prices $(\widehat{a}, \widehat{b})$ 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 $(\frac{1}{2}, \frac{1}{2})$. 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 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

[5] Shopping for better quotes among multiple dealers would provide the customer with better B2C execution. We assume search friction here which prevent this.

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 volatility ϵ^2 of the midprice process x_t.

It is useful to denote standardized ask and bid quotes by $a = \widehat{a} - x_t$ and $b = \widehat{b} - x_t$, respectively.[6] 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,

$$\begin{aligned} F^a\left(R^a \geq \widehat{a}\right) &= F^a\left(R^a - x_{t+1} \geq \widehat{a} - x_{t+1} = a - \Delta x_{t+1}\right) &= 1 - ad + d\Delta x_{t+1} \\ F^b(R^b \leq \widehat{b}) &= F^b(R^b - x_{t+1} \leq \widehat{b} - x_{t+1} = b - \Delta x_{t+1}) &= 1 + bd - d\Delta x_{t+1}, \end{aligned}$$

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 $S = \widehat{A} - \widehat{B} > 0$.

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 $\widehat{A}$ and sell at the (best) bid price $\widehat{B}$. The inter-dealer prices are cointegrated with the price process x_t with $\widehat{A} = x_t + \frac{S}{2}$ and $\widehat{B} = x_t - \frac{S}{2}$. We refer to standardized inter-dealer prices as $A = \widehat{A} - x_t = \frac{S}{2}$ and $B = \widehat{B} - x_t = -\frac{S}{2}$, respectively and assume $\frac{S}{2} \in [0, \frac{1}{d}]$. 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 τ per transaction for liquidity providers.[7]

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. An important aspect of the analysis is to develop the (endogenous) equilibrium spread

[6] Hereafter, the expression 'standardized quotes' means the deviation of the quote from the prevailing B2B mid-price.

[7] MTS charges dealers a fee for executed limit orders proportional to trading volume. This brokerage fee may decrease in a dealer's overall MTS trading volume, but details on volume discounts were not disclosed to us. We assume for simplicity a fee structure that is constant for each unit of executed limit order supply.

S under a competitive inter-dealer market structure. A competitive market structure implies that identical 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 $(\widehat{a}, \widehat{b})$ 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 $0 < \beta < 1$ denote the dealer's discount factor.

In order to limit the number of state variables we allow for only three inventory levels. This choice greatly facilitates the exposition.[8] 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)).

We summarize the sequence of trading in Figure 1. 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.

2.2 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

[8] It is possible to generalize the model to more inventory states at the cost of a more cumbersome exposition. On the other hand, all analytical insights are preserved under the most parsimonious structure of only three inventory states.

$p_{s_t s_{t+1}}$ 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

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

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

$$\mathbf{V}(s, x_t) = \begin{bmatrix} V(1, x_t) \\ V(0, x_t) \\ V(-1, x_t) \end{bmatrix} = max_{\{\widehat{a}(s), \widehat{b}(s)\}} \beta \mathcal{E}_t \left[\mathbf{M} \ \mathbf{V}(s, x_{t+1}) + \widetilde{\mathbf{\Lambda}} \right] \tag{1}$$

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

$$\widetilde{\mathbf{\Lambda}} = \begin{bmatrix} \widetilde{\Lambda}(1) \\ \widetilde{\Lambda}(0) \\ \widetilde{\Lambda}(-1) \end{bmatrix} = \begin{bmatrix} \left[\widehat{B} - \widehat{b}(1) \right] p_{12} + \widehat{a}(1) p_{10} + r x_t \\ -\widehat{b}(0) p_{01} + \widehat{a}(0) p_{0-1} \\ -\widehat{b}(-1) p_{-10} + \left[\widehat{a}(-1) - \widehat{A} \right] p_{-1-2} - r x_t \end{bmatrix}.$$

The payoff in state $s = 1$ includes the profit $\widehat{B} - \widehat{b}(1)$ if a dealer's bid quote is executed (which occurs with probability p_{12}) and the expected profit $\widehat{a}(1) p_{10}$ if the ask quote is accepted by a customer. Analogous explanations apply to the other two states. The terms $r x_t$ and $-r x_t$ 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.[9]

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

[9] For the interest rate r we assume $1/(1+r) = \beta$. The rate of interest equals the rate of time preference. This assumption assures that the value function takes on its simple linear form expressed in proposition 1.

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:

$$\begin{array}{rclcl} V(1, x_{t+1}) & = & V(1, x_t) + \Delta x_{t+1} & = & V - \nabla + x_{t+1} \\ V(0, x_{t+1}) & = & V(0, x_t) & = & V \\ V(-1, x_{t+1}) & = & V(-1, x_t) - \Delta x_{t+1} & = & V - \nabla - x_{t+1} \end{array} , \tag{2}$$

where V and ∇ are two positive parameters.[10]

Proof: See online Technical Appendix A.[11]

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 $V(-1, 0) = V(1, 0) < V(0, 0)$. 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 ∇ characterizes the concavity of the value function with respect to the inventory level. It embodies a dealer's value loss due to inventory constraints.

[10] A neccessary condition for existence is the usual transversality condition which requires that the present value of the future payoff be bounded.

[11] http://www.haraldhau.com or http://www.qub-efrg.com/faculty-directory/6/michael-moore/

2.3 Optimal B2C Quotes

The first order conditions are obtained by differentiating the value function (1) with respect to the bid and ask prices $(\widehat{a}(s), \widehat{b}(s))$ 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 ∇, 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 ∂a has two opposite effects. It increases the expected profit on prospective sell transactions that have a likelihood of $qF^a\left(R^a - x_{t+1} \geq a(1) - \Delta x_{t+1}\right) = q\left(1 - a(1)d + d\Delta x_{t+1}\right)$ for the current period. This implies an expected profit increase of $q\left[1 - a(1)d\right]\partial a$. 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

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

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 $0 < S < \frac{2}{d}$ and inventory state s, there exists a unique optimal ask and bid quote $(a(s), b(s))$ given by

$$\begin{bmatrix} a\,(-1) \\ a\,(0) \\ a\,(1) \end{bmatrix} = \begin{bmatrix} \frac{1}{2d} \\ \frac{1}{2d} \\ \frac{1}{2d} \end{bmatrix} + \frac{1}{2}\begin{bmatrix} \frac{S}{2} \\ \nabla \\ -\nabla \end{bmatrix} \text{ and } \begin{bmatrix} b\,(-1) \\ b\,(0) \\ b\,(1) \end{bmatrix} = \begin{bmatrix} -\frac{1}{2d} \\ -\frac{1}{2d} \\ -\frac{1}{2d} \end{bmatrix} + \frac{1}{2}\begin{bmatrix} \nabla \\ -\nabla \\ -\frac{S}{2} \end{bmatrix} \tag{3}$$

which depend linearly on the concavity parameter ∇ and the inter-dealer spread S. The value function of a dealer follows as the perpetuity value of her future expected payoffs Λ_0 and the expected adverse selection losses $\mathbf{\Phi}$. Formally,

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

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

Proof: See online Technical Appendix B.[12]

Equation (4) implicitly defines the concavity parameter ∇ 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 2 as the B2C equilibrium schedule in a space spanned by $\frac{S}{2}$ and ∇. The concavity parameter ∇ 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 ∇ 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 ∇) in an effort to avoid costly B2B rebalancing. The next section develops the equilibrium condition for the inter-dealer market.

2.4 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.[13] 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 ∇ by increasing their inventory level to zero and dealers with a positive inventory position *also* gain ∇ by decreasing their inventory to zero. Hence, dealers with a short inventory position will provide the most competitive inter-dealer bid B while dealers

[12] http:// www.haraldhau.com or http://www.qub-efrg.com/faculty-directory/6/michael-moore/

[13] 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.

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 ∇ 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 ϵ. 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 ϵd 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 Δx_{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 B2B half-spread $\frac{S}{2}$.

Proposition 3 : Competitive B2B Quotes

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

$$L = L^A = L^B = \frac{2\epsilon^2}{\frac{1}{d} - \frac{S}{2}} > 0.^{14}$$

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

[14] Recall that the properties of the uniform distribution require that the denominator be positive.

by

$$A = \max(L - \nabla + \tau, 0) = \frac{S}{2}, \quad B = \min(-L + \nabla - \tau, 0) = -\frac{S}{2} \tag{5}$$

respectively, where τ represents the order processing costs of the liquidity provider and ∇ denotes the concavity parameter of the dealers' value function.

Proof: See online Technical Appendix C.[15]

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.

Not surprisingly, the (adverse selection) loss function L is increasing in the variance ϵ^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 Δx_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 ∇ by moving to a zero inventory if execution occurs. Under the competitive market assumption 2, her expected conditional profit is zero,

[15] http://www.qub-efrg.com/faculty-directory/6/michael-moore/

hence $A+\nabla-L-\tau=0$, where τ 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 ∇ of rebalancing. Only dealers who run against the inventory limits at ± 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 ∇ 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 2 with the label B2B. Its intercept and turning point are derived in the online Technical Appendix D.[16]

For a low B2B spread S, an increase in the concavity parameter ∇ comes with a decrease in the B2B spread. Intuitively, the most competitive B2B quote is provided on the ask side by dealers with positive inventory and on the bid side by dealers with negative inventory. A successful B2B transaction moves the dealer in both cases to the zero inventory state and the associated value gain is given by ∇. Under competitive B2B bidding, a higher value gain from rebalancing (through limit orders) implies a lower B2B spread. Hence the (initial) negative link between S and ∇, because higher rebalancing costs through market orders (captured by S) make B2B limit order submission (with its benefit ∇) more attractive. But the endogenous adverse selection effect starts to dominate as B2B spread becomes larger. For a high B2B spread S, inventory shading in the B2C segment (at the inventory limit) becomes more pronounced. As a consequence, the information content of market orders in the B2B market and their adverse selection risk increases; this requires an increase in S even as ∇ increases. This positive relationship between S and ∇ for high adverse selection risk is depicted by the right branch of the parabola labeled B2B in Figure 2.

2.5 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

[16] http://www.haraldhau.com or http://www.qub-efrg.com/faculty-directory/6/michael-moore/

depends on the concavity parameter ∇ 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 2 as the intersection of the B2B and B2C graphs. Figure 2 highlights that there could be up to two equilibria. We label the equilibrium where both $\frac{S}{2}$ and ∇ are high as Z_U, in contrast to the equilibrium Z_L with low values of $\frac{S}{2}$ and ∇. 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 volatility ϵ^2 below some threshold $\bar{\epsilon}^2$, there exists a single stable equilibrium pair $(\frac{S}{2}, \nabla)$ for the B2B spread S and the convexity of the dealer value function ∇, such that (i) dealers make optimal customer quotes as stated in proposition 2, and (ii) these quotes imply a value function with convexity ∇ so that S is the competitive B2B spread as stated in proposition 3.

Proof: See online Technical Appendix D.[17]

The uniqueness of the stable equilibrium Z_L allows us to undertake comparative statics with respect to the price volatility ϵ^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 2 show that a volatility increase (higher ϵ^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 τ, which also shifts the B2B schedule upwards. Again, the inter-dealer

[17] http://www.haraldhau.com or http://www.qub-efrg.com/faculty-directory/6/michael-moore/

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 τ – for example an exogenous security transaction tax – can induce a disproportionally 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 τ. 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 ∇, which remains positive. For zero order processing costs ($\tau = 0$), the competitive inter-dealer spread becomes zero. Second, consider a high level of price volatility given by $\epsilon^2 = \frac{1}{4d^2}$. At this level of volatility the B2C equilibrium schedule degenerates to a single point $(\frac{1}{d}, 0)$ 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.

3 Overview of the European Sovereign Bond Market

3.1 Market Structure

The European sovereign bond market is the world's largest market for debt securities.[18] With an outstanding aggregate value of approximately €4,395.9 billion in 2006, it exceeds the size of the U.S. sovereign bond market with an aggregate value of roughly U.S.$4,413.5 billion (around €3 trillion, at the time). The European market has as many issuers as countries and the outstanding value differs greatly across issuers. Table 1 provides an overview of the outstanding value by issuing country. The largest issuer is the Italian treasury with an outstanding sovereign debt of €1,213 billions [19] in 2005,

[18] This was certainly true during the span of the data we analyze. The relative importance of the U.S. and Euro-zone markets has oscillated back and forth since then.

[19] Table 1 only includes debt with a maturity in excess of 1.5 years. Italy also issues a substantial volume of short-dated securities.

followed by Germany and France.[20]

The market structure in the European sovereign bond market corresponds to the two tier structure captured in our model of dealer intermediation. The market participants 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. MTS has different shares of the inter-dealer market in different countries. Its largest market share is in Portugal and Italy, where it has close to 100 percent. In the case of Italy, the dominant position of MTS is explained by market regulation which stipulates that for monitoring purposes, all inter-dealer trades have to occur on the MTS platform. In other countries MTS has a lower market share, as shown in the last column of Table 1. 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. It is dedicated to inter-dealer trading and customers do not have access. We therefore refer to MTS trades as B2B transactions. MTS dealers are mostly so-called 'primary dealers,' that is, they face two-sided quoting obligations in exchange for privileged consideration when it comes to new bond issues. Primary dealers are usually allowed a maximum spread size in long maturity bonds of 7 basis points. However, this seems quite large when compared to the average inside spread of approximately 3 basis points.

Trading in the dealer-customer (B2C) segment of the market has traditionally been conducted 'over-the-counter' by individual dealers in bilateral phone contact with their customers. The B2C segment has remained opaque while the inter-dealer segment is very transparent in terms of pre- and post-trade information. Over-the-counter (OTC) trading in the B2C segment has been declining but according to interviews with participants it remains a significant fraction of all B2C transactions and it increases in times of market stress (Dunne, Moore, and Portes, (2006)).[21] At the time of our study,

[20] For more institutional background, see also Dunne et al. (2006, 2007).

[21] Even in the case of OTC trading, customers usually have access to pre-trade information from their dealer via electronic means. In early versions of electronic access, dedicated screens had to be installed to access pre-trade information from specific dealers. The fixed costs associated with these arrangements meant that customers chose a sub-set of the available platforms and competition was driven more by the quality of the electronic equipment available to customers and the costs associated with switching from one platform to another rather than the competitiveness of pricing for individual deals. This situation afforded a large degree of market power to those dealers who were the earliest developers and adopters of quality communications technology. The effects of switching costs is examined by Foucault and Menkveld (2008). This structure changed with the adoption of internet-based communications technology, which enabled larger customers to subscribe to more information feeds and brought dealers into direct competition with each other on a deal-by-deal basis. The structure again changed markedly in more recent years when even more integrated and actionable systems were set up by TradeWeb, MTS (BondVision), Eurex and to some extent Bloomberg (called Bloomberg Bond

various B2C trading platforms coexisted. 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 were now 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. It was widely understood that TradeWeb had a slightly larger share of the B2C market in Euro-denominated bonds than BondVision. However, BondVision was operated by MTS in parallel with the inter-dealer platform and thus it was easier to compile consistent and accurate time-stamped data from the two segments by using BondVision data. Despite its being a small fraction of all customer-dealer trading in Euro-denominated bonds, we believe that BondVision provides a representative sample of the B2C segment in terms of the quality of pricing.

On BondVision dealers are not required to provide quotes when requested, nor are customers obliged to accept any submitted quote. An important feature of the BondVision platform is that the identity of customers is revealed on request submission. Also, while dealers know when there is a request from multiple dealers they do not know who the other dealers are and they are only informed about their performance in auctions if they provided the second-best quote. The customer option to transact on any dealer quote expires after 90 seconds but for most accepted quotes transactions occur within the first 30 seconds. Customers may have trading relationships with more than one of the many registered dealers who provide prices on request on the BondVision platform.[22] The degree of competition matters for the quality of pricing and we document this.

3.2 MTS and BondVision Data

As intimated above, we explore a new data set that combines both inter-dealer (B2B) and dealer-customer data (B2C). The B2B data are sourced from the MTS inter-dealer electronic platform while the dealer-to-customer data come from the BondVision request-for-quote system.[23] The BondVision system is also owned by MTS. 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

Trader or BBT).

[22] For example, there are 35 dealers authorized to trade Italian bonds.

[23] The MTS B2B platform operates on a country-specific basis as well as at a pan-Euro-area level where only the Euro-benchmark bonds are traded. This introduces the possibility of fragmentation since some bonds can be traded on both platforms. However the analysis by DeJong et al. (2004) did not find any significant fragmentation from this source and in our analysis we do not distinguish between trading or quoting that takes place simultaneously on parallel MTS platforms.

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 quotes made to 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.

The total volume[24] traded for the last three quarters of 2005 in the B2C BondVision platform was €240.22 billion spread over 45,504 trades or just over €2 billion per day. Volume in the B2B segment was €1,369 billion spread over 188,782 trades. Volume in the B2B was therefore about 5.7 times B2C volumes. The smaller B2C volume may largely reflect the fact that a significant proportion of B2C activity occurs in the OTC market or on other electronic platforms, such as Tradeweb and Bloomberg Bond Trader (BBT). Despite the fragmentation of the market the BondVision platform represents a significant proportion of B2C electronic requests for quote (RFQ) trading. This is particularly true for Italian issues, where conversations with dealers suggest that a particularly high proportion of B2C trading occurs on BondVision. 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.

Table 2 provides summary statistics on the B2B and B2C segment of the Italian and non-Italian bonds for the last three quarters of 2005. Over this 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. These bonds are generally of particularly high liquidity but they are not as uniquely defined as 'on-the run' bonds in the U.S. Treasury market.[25] Indeed, there are typically multiple benchmarks bonds at each stage of maturity and even within the maturity bucket of a single country. 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. Each maturity group from the same issuer represents bonds that are presumably close substitutes so that they can be pooled for the purpose of our transaction cost analysis.

The liquidity is high in most bonds and relatively constant over the nine months of the sample.

[24] We have excluded very short dated (<1.5 years to maturity) securities from our data set because of the impracticality of calculating statistics and regression coefficients for bonds that mature within our sample time period.

[25] In terms of the number of trades per month, we detected only a slight 'on-the-run' effect for the most recently issued bond. This contrasts with the pronounced 'on-the-run' liquidity effects observed by Barclay et al. (2006) in the U.S. Treasury market. For additional work on the liquidity in the U.S. Treasury market see Fleming and Remolona (1999) and Brandt and Kavajecz (2004).

High liquidity at the inside spread justifies why we ignore market depth as an additional measure of B2B market quality. There is virtually no difference between the quoted and transacted spread as the available liquidity at the inside spread almost always exceeds any market order size.

3.3 Transaction and Quote Quality in the B2C Market

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 bid price. We refer to this price difference as cross-market spread, defined as

$$\begin{aligned}\text{Cross-Market Spread (Ask)} &= \text{Best B2B Ask Price} - \text{B2C Ask Price} \\ \text{Cross-Market Spread (Bid)} &= \text{B2C Bid Price} - \text{Best B2B Bid Price.}\end{aligned}$$

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 3 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. We separate out Italian bonds because of their overall prominence in MTS's B2B and B2C trading platforms, as is clear from Tables 1 and 2. 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 mean of the observations within each quartile is a smoother measure of spread variation compared to the quartile limits. We found that the quartile limit was afflicted by tick size clustering and was therefore frequently relatively insensitive to differences in the spread distribution.

The insight from Table 3 concern 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. These trades even occur on terms (on average) more favorable than the best B2B ask quote. On the bid side, B2C trades are slightly less favorable. The 25 percent worst trades show an average transaction price outside the B2B spread. 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.[26] 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. Such quality dispersion of B2C trades can be explained by 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 ($\approx$ 1.98 basis points) and can be compared to the average cross-market spread of 1.99 cents ($\approx$ 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.[27]

One may suspect that any comparison between quoted B2B prices and executed B2C prices introduces a selection bias, resulting in the positive cross-market spreads. B2C quotes might be executed when they are particularly favorable relative to the B2B quotes. But this 'execution' bias can be easily examined by comparing non-executed B2C quotes to the simultaneous B2B quotes. The B2C data on RFQs reveal that 32 percent of Italian RFQs resulted in non-execution of the received best quotes by customers. While non-executed B2C prices are less favorable than their executed counterpart, they still tend to be very good relative to the corresponding B2B quotes. Thus, for the entire sample of RFQs we found that 47 percent of executed B2C bids were better than the prevailing B2B bids at the times of B2C execution and that this declined only slightly for non-executed best B2C bids, to 39 percent. On the ask side the proportion of more favorable prices available in the B2C market fell from 80 percent for executed to 74 percent for non-executed.[28] A more plausible explanation for the

[26] We concede that such an absolute evaluation of B2C trade quality (relative the the best B2B spread) poses some issues. B2C trades are on average smaller and also order processing costs might differ across the electronic trading systems.

[27] Our findings here contrast with Vitale (1998) who studies the U.K. gilt market and reports that customer transactions are substantially more costly than inter-dealer trades. However, unlike the European sovereign bond market, the 'opaque' inter-dealer market in U.K. gilts features low market transparency, which is likely to impair customer price discovery.

[28] Additonal tables based on non-executed B2C quotes by country and maturity are available in an earlier version of this paper and from the authors upon request. The same information compared at the times of quote requests and at

positive cross-market spread is the higher volume-based order processing costs charged by MTS for B2B transactions relative to B2C transactions.[29]

3.4 Can Customer Discrimination Explain the Price Dispersion?

An alternative 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 3 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 4 presents cross-market spreads for 171 benchmark bonds (Italian and non-Italian) classified by three maturity groups. 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 that 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 is determined by a dealer's inventory management concerns rather than a customer based price discrimination. In the following section we linearize the model and test its predictions with a more structural approach.

4 Empirical Model Implications

4.1 A Linearized Model Solution

It is straightforward, though tedious, to solve equations for the B2B and B2C spreads. A more informative representation is obtained by a simple linearization of the model.

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the times of acceptance of executed quotes is available. There are only very slight differences in the results for the two alternative choices of when to observe the difference between the two markets.

[29] MTS competes for B2C trades with similar platforms and also with 'free' B2C voice brokerage. As a consequence, MTS cannot charge high order processing fees, unlike its B2B trades. Unfortunately, we were not able to obtain reliable data on the fee structure of MTS as this varies by dealer.

Proposition 5: **Linear Equilibrium Approximation**

A linear approximation to the joint market equilibrium implies inventory-dependent optimal B2C quotes that are linearly dependent on market volatility $Vol = \epsilon^2$ according to

$$
\begin{array}{lllllll}
a(-1) & = & \gamma_{1c} + \gamma_{1v} \times Vol & \quad & b(-1) & = & -\gamma_{3c} \\
a(0) & = & \gamma_{2c} & & b(0) & = & -\gamma_{2c} \\
a(1) & = & \gamma_{3c} & & b(1) & = & -\gamma_{1c} - \gamma_{1v} \times Vol
\end{array}
\tag{6}
$$

and a B2B half-spread given by

$$
\tfrac{1}{2}S = \tfrac{1}{2}(A - B) \quad = \quad \gamma_{4c} + \gamma_{4v} \times Vol \ , \tag{7}
$$

where the parameters fulfill $\gamma_{1c} > \gamma_{2c} > \gamma_{3c} > 0$; $\gamma_{2c} > \gamma_{4c} > 0$ and $\gamma_{4v} > \gamma_{1v} > 0$.

Proof: See online Technical Appendix E.[30]

The B2C spread shows a volatility dependence that differs across inventory states. The most unfavorable ask side quote $a(-1)$ increases in volatility and the most unfavorable bid side quote $b(1)$ decreases in volatility. The volatility dependence in these two inventory states reflects the volatility dependence of the B2B spread. In both inventory states it is possible that the dealer has to resort to the B2B market if the respective B2C quotes are executed. To avoid trading losses, the B2C quotes deteriorate in volatility. But the volatility dependence of the B2B spread is nevertheless much stronger than for the B2C quotes $a(-1)$ and $b(1)$ as $\gamma_{4v} > \gamma_{1v}$. The four B2C quotes $a(0) > a(1) > b(-1) > b(0)$ are constant in volatility under the linear approximation. Intuitively, the market power of the dealer implies a monopolistic B2C quote with a constant price mark-up determined by the distribution of reservation prices. The mark-up largely absorbs the adverse selection effect under increasing volatility except for the outside quotes $a(-1)$ and $b(1)$, which have to account for the probability of rebalancing in the B2B market.

The competitive nature of the B2B market, on the other hand, fully reflects the adverse selection effect and therefore features a strong volatility dependence. The finding of a strong volatility dependence in the B2B spread and a weak volatility dependence in the B2C spread implies the following:

[30] http://www.haraldhau.com or http://www.qub-efrg.com/faculty-directory/6/michael-moore/

Corollary 1: Volatility Dependence of the Cross-Market Spread

Higher volatility improves the quality of the average B2C trade $(\overline{a}, \overline{b})$ relative to the B2B spreads (A, B) as measured by the average cross-market spreads, $\overline{a} - A$ and $-\overline{b} + B$, respectively. The average cross-market spread decreases in volatility both on the ask and bid sides of the market.

Proof: See online Technical Appendix E.[31]

The Corollary 1 concerns the average cross-market spread as a function of volatility. But it is also clear from Proposition 5 that the dispersion of the cross-market spread increases in market volatility as the price difference $a(-1) - a(1)$ and $b(-1) - b(1)$ between best and worst B2C quotes increases. As bond maturity is another proxy for price volatility and adverse selection risk faced by the dealer, we also expect that the dispersion of cross-market spreads increases in the bond maturity as documented in Table 4.

4.2 Evidence on the Volatility Dependence of the Spread

This section applies regression analysis to test for the negative volatility dependence of the cross-market spread predicted in Corollary 1. A linear regression is proposed as follows:

$$\begin{array}{rcccl} \text{Cross-Market Spread (Ask)} & = & A - a & = & \mu_{a0} + \mu_{av} \times Vol + \eta_a \\ \text{Cross-Market Spread (Bid)} & = & b - B & = & \mu_{b0} + \mu_{bv} \times Vol + \eta_b \end{array},$$

where η_a and η_b are i.i.d. processes, μ_{a0}, μ_{av}, μ_{b0} and μ_{bv} are parameters. Corollary 1 implies parameter estimates $\mu_{av} = \mu_{bv} > 0$.

A potential problem with this regression is simultaneity bias. For example, relatively high realizations of the best B2B ask quote A change the cross-market spread on the ask side positively. But this simultaneously increases the volatility measure based on variations of the mid-price $MidP = \frac{1}{2}(A+B)$. An instrumental variable approach is needed to eliminate this simultaneity bias in the regression. Lagged volatility is fortunately a very good instrument for the contemporaneous volatility measure and it is therefore used in the regression. We also include fixed effects for each bond to control for heterogeneity across bonds.

In Table 5, columns (1) and (3) 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

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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. Before we consider effects covered by our theory it is interesting to note that our control variables give significant results. The cross-market spread is significantly negatively related to the log of B2C transaction size in all cases. This is consistent with the view that large-sized trades are more likely to be from informed customers and that such adverse selection risk is priced. Alternatively, larger trades may pose greater challenges in terms of inventory management and therefore encounter less favorable B2C execution. However, this finding is difficult to reconcile with the hypothesis of dealer discrimination across customer sophistication as long as smaller trade size proxies for less customer sophistication.

Competition effects are controlled for by the use of separate intercepts for RFQs from a single dealer and RFQs from more than one dealer; in all cases, these indicate that competition improves pricing for the customer. The regression results of most relevance to the theoretical model are consistent with the model. 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 both the full sample and the subsample of long maturity bonds. The behavior of the bid side spread is therefore fully consistent with the model prediction. For the ask side, we cannot confirm that the predicted cross-market spread increases in volatility. On the other hand we do not find any negative volatility effect, either. Hence, there is no change in the B2C ask side trade quality (relative to the best B2B quote) as volatility changes.

The B2B spreads in Table 5, columns (5) and (7), 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 0.590 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. Next, we look at the central issue of inventory imbalances and their role in the determination of the B2C quotes.

4.3 Aggregate Inventory Imbalances and B2C Trades

An 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. We can therefore infer the aggregate inventory imbalances from the B2B market and verify empirically whether inventory imbalances have the predicted role for the B2C quotes. For example, a large depth in the B2B market at the inside ask quote indicates willingness of many traders to sell and this should occur under undesirable positive inventory, namely the state $s = 1$ for many dealers.

To obtain an empirical counterpart to inventory imbalances, consider that n dealers compete in the B2B market for liquidity supply. Their distribution over the three inventory states $s = -1, 0, 1$ is denoted by $n(-1)$, $n(0)$ and $n(1)$, respectively. We define the imbalance toward positive inventory as

$$Imb = \frac{n(1) - n(-1)}{n(1) + n(-1)},$$

where $-1 \leq Imb \leq 1$. Since each of the dealers in states $s = -1$ and $s = 1$ submits a unit quantity of liquidity at the best B2B bid and ask price, respectively, we can directly measure the variable Imb without observing dealer-specific inventory states.

We can express the (conditional) probability distribution of traders over the three inventory states as a function of the variable Imb. The share of traders with a balanced inventory can be defined as

$$c_t = \frac{n(0)}{n(1) + n(0) + n(-1)}$$

and the expected share as $E(c_t) = \bar{c}$. The number of dealers with unbalanced inventories follows simply as $n(1) + n(-1) = (1 - c_t)n$. The probability of a particular trader to be in state s is given by

$$p(s) = p(s, Imb, \bar{c}) = \begin{cases} E\left[\frac{n(1)}{n}\right] & = & \frac{1-\bar{c}}{2}(1 + Imb) & \text{for} & s & = & 1 \\ E\left[\frac{n(0)}{n}\right] & = & \bar{c} & \text{for} & s & = & 0 \\ E\left[\frac{n(-1)}{n}\right] & = & \frac{1-\bar{c}}{2}(1 - Imb) & \text{for} & s & = & -1 \end{cases} . \tag{8}$$

A high value for imbalances Imb therefore implies a relatively higher expected probability that a representative dealer is in inventory state $s = 1$ and a lower expected probability that he is in state $s = -1$.

An attractive feature of the aggregate imbalance variable Imb is its observability in the B2B order book data. According to our model, each dealer with a positive inventory submits an ask quote A

in the B2B market at the best inside quote. The total liquidity available at the best ask is therefore proportional to the number of dealers with inventory $s = 1$. The same holds for dealers in state $s = -1$, who are the liquidity suppliers at the best B2B bid. We can therefore measure aggregate inventory imbalances as

$$Imb = \frac{Q(Ask) - Q(Bid)}{Q(Bid) + Q(Ask)}$$

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

The average B2C quotes $(\overline{a}, \overline{b})$ depend on the distribution of inventory states $p(s)$. Formally, we have

$$\overline{a} = \sum_{s=-1,0,1} p(s)a(s)g(a(s)) \quad \text{and} \quad \overline{b} = \sum_{s=-1,0,1} p(s)b(s)g(b(s)),$$

where $p(s)$ represents the probability of inventory state s. The functions $g(a(s)) = 1 - a(s)d$ and $g(b(s)) = 1 + b(s)d$ denote the probabilities that customer quotes $a(s)$ and $b(s)$ are accepted. A positive inventory imbalance implies that relatively more dealers are in state $s = 1$ and this implies in turn that more customers receive favorable ask quotes $a(1)$ and unfavorable bid quotes $b(1)$. The expected B2C ask and bid transaction prices $(\overline{a}, \overline{b})$ should therefore decrease in the inventory imbalance Imb.

Figure 3, panel A plots the average cross-market spread $A - \overline{a}$ on the ask side as a function of the inventory imbalance and the volatility. The corresponding cross-market spread $\overline{b} - B$ 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 3 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 $\overline{a}$ 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 $s = 1$, as described in equation (8). 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 dependence of the cross-market spread on both volatility and the inventory imbalance is summarized as follows:

Proposition 6: Transaction Spreads under Dealer Inventory Imbalances

The cross-market spreads on the ask and bid side can be linearly approximated by

$$\begin{array}{rcccl} \text{Cross-Market Spread (Ask)} & = & A - a & = & \mu_{a0} + \mu_{av} \times Vol + \mu_{aI} \times Imb + \eta \\ \text{Cross-Market Spread (Bid)} & = & b - B & = & \mu_{b0} + \mu_{bv} \times Vol + \mu_{bI} \times Imb + \eta \end{array},$$

where we expect for the coefficients $\mu_{av} = \mu_{bv} > 0$ and $\mu_{aI} = -\mu_{bI} > 0$.

Proof: See online Technical Appendix E.[32]

Previous work has found evidence for inventory effects on prices in equity and future markets. Hasbrouck and Sofianos (1993), for example, find evidence that inventory shocks influence the quote behavior of NYSE specialists. Manaster and Mann (1996) confirm inventory price effects in futures trading and Lyons (1997) for a single FX dealer. The following section takes up this issue for the European sovereign bond market.

4.4 Evidence on the Role of Aggregate Dealer Imbalances

Extending the previous regression on the nexus between volatility and spreads to inventory imbalances is straightforward. 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.

In Table 5, columns (2) and (4) we present the regression results for the inventory dependence of the cross-market spread once again including controls for competition and transaction size. The control variables do not require further discussion as they do not change much from the case that excluded the imbalance variable. Panel A reports the regression results for the ask side and panel B for the bid side. In each case we run a regression for the full sample of all 13 liquid Italian government bonds and the subsample of six very liquid long-dated Italian government bonds. The estimation coefficients have the signs predicted in proposition 6 and are therefore consistent with the numerical results depicted in Figure 3. The point estimates for the volatility dependence of the spread are very similar to those in columns (1) and (3). The imbalance measure is almost orthogonal to the volatility measure and its inclusion in the regression is without consequence for the spread-volatility nexus.[33]

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 predicted by proposition 6. The intuition is simple. A large number of

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[33] The correlation between imbalances and volatility for the long-dated bonds is miniscule at 0.0076.

dealers with positive inventory will tend to increase the liquidity available at the best ask relative to the best bid and therefore generate a positive realization for the imbalance measure. But a positive inventory imbalance by the majority of traders will also imply that the average B2C quote is very favorable on the ask side and very unfavorable on the bid side . As a consequence, the cross-market spread should *ceteris paribus* be high on the ask side and low on the bid side of the market, as depicted in Figure 3.

Finally, we highlight that the point estimates, in absolute value, for imbalances between 0.313 and 0.477 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 5 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. Inventory imbalances proxied by liquidity imbalances in the B2B market therefore explain economically significant variations in B2C transaction price quality.

5 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 ∇, 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 3 and 4 show somewhat more favorable cross-market spreads on the ask than on the bid side. One straightforward explanation could be more dense distribution of customer reservation prices 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 ∇_a and ∇_b influencing ask and bid side quotes differently. While this is still rather tractable and can capture bid- and ask-side asymmetry, the fundamental insights of the models are not altered.

A still more desirable extension would be the introduction of dealer competition for customer quotes. But such an extension unfortunately 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 section 4.4. 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 is therefore technically difficult to introduce inter-dealer competition for customer quotes into our framework. But we may assess the consequences of more inter-dealer competition on an intuitive level: It should diminish the B2C price mark-ups and therefore favor customers. The extremely competitive B2C transaction prices discussed in Table 4 suggest that a dealer's market power in the B2C segment might be more limited than our monopolistic assumption suggests.

6 Conclusions

Microstructure research has typically framed a dealer's intermediation problem within a single market that enables both liquidity provision and inventory rebalancing. A two-tier market structure in many financial markets separates both functions — as is the case for the European bond market. Liquidity provision for customers occurs through requests for quote systems like BondVision, while electronic inter-dealer platforms like MTS primarily serve dealers' rebalancing needs. Customers generally do not have direct market access to the inter-dealer platform. The dealer is therefore an 'interface' between a centralized B2B market and a group of potential customers.

This paper develops a new and tractable model to analyze the interdependence of optimal price setting behavior in both market segments. Dealers face inventory constrains and adverse selection. We characterize the role of rebalancing costs in the B2B segment for a dealer's optimal price shading policy in the B2C segment. Higher B2B spreads increase rebalancing costs and increase B2C price shading. Inversely, we show that for low B2B spreads, higher costs of inventory constraints can actually reduce B2B spreads; but that in a range of large B2B spreads, higher inventory costs re-enforce the adverse selection risk in the B2B segment, generating higher spread and for some parameters market breakdown. To our knowledge, it is the first model to derive the competitive B2B limit order process from the B2C market structure and determines its adverse selection component endogenously based on optimal dealer price shading in the customer-dealer segment.

The model is tested for synchronized price data from both the B2B and B2C segment of the European sovereign bond market. The price difference between the B2C price and the best B2B quote is referred to as the cross-market spread and measures B2C transaction quality. We find a large dispersion of the cross-market spread as predicted by a model with inventory contingent B2C price quotes. Moreover, the dispersion of the cross-market spread increases dramatically in bond maturity — a proxy for bond price volatility and adverse selection risk. The strong risk dependence of the B2C quote quality is at odds with the alternative explanation which interprets this quality dispersion as a result of by price discrimination across different customer type.

We also test the more structural model implications. B2C trade quality measured by the cross-market spread should improve under higher market volatility. We find this prediction confirmed for the ask side, whereas this effect is insignificant on the bid side of the European sovereign bond market. Intuitively, B2B spreads are set competitively so that higher adverse selection risk associated with high volatility is fully reflected in B2B spreads. By contrast, monopolistic price mark-up in the B2C segment can absorb some the adverse selection risk of higher market volatility. More direct evidence that inventory management concerns relate the two market segments is provided by the aggregate imbalance statistics for the B2B market. Our model implies that dealers with a positive inventory imbalance tend to submit limit orders at the best ask and dealers with a negative inventory post liquidity at the best bid. The relative depth of the limit order book at the best bid relative to the best ask therefore proxies for the aggregate inventory imbalance among all dealers. We show that the inferred measure of inventory imbalances is indeed a strong predictor of B2C transaction quality. A positive inventory imbalance decreases customer trade costs on the ask side and increases customer trade costs on the bid side. The dealer inventory effect is both statistically and economically significant for the quality of B2C transactions. The inventory management concerns of primary dealers can explain an economically significant proportion of the high quality dispersion of customer trades.

References

[1] Amihud; Y. and H. Mendelson. "Dealership Markets: Market Making with Inventory". *Journal of Financial Economics*, 8 (1980), 31-53.

[2] Biais, B.; L. Glosten; and C. Spatt. "Market Microstructure: A Survey of Microfoundations, Empirical Results, and Policy Implications". *Journal of Financial Markets*, 8 (2005), 217-264.

[3] Barclay, M. J.; T. Hendershott; and K. Kotz. "Automation versus Intermediation: Evidence from Treasuries Going Off the Run". *Journal of Finance*, 61, 5 (2006), 2395-2414.

[4] Bernhardt, D.; V. Dvoracek; E. Hughson; and I. Werner. "Why Do Larger Orders Receive Discounts on the London Stock Exchange?" *Review of Financial Studies*, 18 (2005), 1343-1368.

[5] Bessembinder, H.; and W. Maxwell. "Markets: Transparency and the Corporate Bond Market." *Journal of Economic Perspectives*, 22, 2 (2008), 217-234.

[6] Bessembinder, H.; W. Maxwell; and K. Venkataraman. "Market Transparency, Liquidity Externalities, and Institutional Trading Costs in Corporate Bonds." *Journal of Financial Economics,* 82, 2 (2006), 251-288.

[7] Biais, B. "Price Formation and Equilibrium Liquidity in Fragmented and Centralized Markets." *Journal of Finance,* 48 (1993), 157-185.

[8] Brandt, M. W.; and K. A. Kavajecz. "Price Discovery In The U.S. Treasury Market: The Impact of Orderflow and Liquidity on the Yield Curve." *Journal of Finance*, 59, 6 (2004), 2623-2654.

[9] DeJong, F.; Y. Chung; and B. Rindi. "Trading European Sovereign Bonds: The Microstructure of the MTS trading platforms, European Central Bank." Working Paper No. 432 (2005).

[10] Dunne, P. G.; M. Moore; and R. Portes. "European Government Bond Markets: Transparency, Liquidity, Efficiency; City of London." Corporation Monograph commissioned from CEPR, http://www.cityoflondon.gov.uk/economicresearch (2006).

[11] Dunne, P. G.; M. Moore; and R. Portes. "Benchmark Status in Fixed-Income Asset Markets." *Journal of Business Finance and Accounting*, 34, 9-10 (2007), 1615–1634.

[12] Edwards, A. K.; L. Harris; and M. Piwowar. "Corporate Bond Market Transaction Costs and Transparency." *Journal of Finance*, 62, 3 (2007), 1421-1451.

[13] Fleming, M. J.; and E. M. Remolona. "Price Formation and Liquidity in the U.S. Treasury Market: The Response to Public Information." *Journal of Finance*, 54, 5 (1999), 1901-1915.

[14] Fleming, M. J.; and B. Mizrach. "The Microstructure of a U.S. Treasury ECN: The BrokerTec Platform." Mimeo, *http://snde.rutgers.edu/wp/[48]-WP_ brokertec.pdf* (2008).

[15] Foucault, T. and A. J. Menkveld. "Competition for Order Flow and Smart Order Routing Systems." *Journal of Finance*, 63, 1 (2008), 119-158.

[16] Goldstein, M.; E. Hotchkiss; and E. Sirri. "Transparency and Liquidity: A Controlled Experiment on Corporate Bonds", *Review of Financial Studies*, 20 (2007), 235-273.

[17] Glosten, L.; and P. Milgrom. "Bid, Ask, and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders" *Journal of Financial Economics*, 14, 1 (1985), 71-100.

[18] Green, R.; B. Hollifield; and N. Schurhoff. "Financial Intermediation and the Costs of Trading in an Opaque Market." *Review of Financial Studies*, 20, 2 (2007), 275-314.

[19] Hansch, O.; Naik, N.; and S. Viswanathan. "Do Inventories Matter in Dealership Markets? Evidence from the London Stock Exchange." *Journal of Finance*, 53, 5 (1998), 1623-56.

[20] Harris, L.; and M. Piwowar. "Secondary Trading Costs in the Municipal Bond Market Preview." *Journal of Finance*, 61, 3 (2006), 1361-1397.

[21] Hasbrouck, J.; and G. Sofianos. "The Trades of Market Makers: An Empirical Analysis of NYSE Specialists" *Journal of Finance,* 48 (1993), 1565-1594.

[22] Hendershott, T.; and A. Menkveld. "Price Pressures." SSRN working paper (2010).

[23] Kyle, A.. "Continuous Auctions and Insider Trading." *Econometrica*, 53, 6 (1985), 1315-1335.

[24] Lyons, R. K.. "A Simultaneous Trade Model of the Foreign Exchange Hot Potato." *Journal of International Economics,* 42 (1997), 275-98.

[25] Madhavan, A.; and S. Smidt. "An Analysis of Changes in Specialist Inventories and Quotations" *Journal of Finance*, 48, 5 (1993), 1595-1628.

[26] Madhavan, A.. "Market Microstructure." *Journal of Financial Markets,* 3 (2000), 2005-258.

[27] Manaster, S.; and S. Mann. "Life in the Pits: Competitive Market Making and Inventory Control." *Review of Financial Studies*, 9 (1996), 953-976.

[28] O'Hara, M., and G. Oldfield. "The Microeconomics of Market Making." *Journal of Financial and Quantitative Analysis*, 21, 4 (1986), 361-376.

[29] Reiss, P.C.; and I. Werner. "Transaction Costs in Dealer Markets: Evidence from The London Stock Exchange." Lo, A., ed.. In *The Industrial Organization and Regulation of the Securities Industry*, University of Chicago Press (1996) 125-176.

[30] Reiss, P.C.; and I. Werner. "Does Risk Sharing Motivate Interdealer Trading?" *Journal of Finance*, 53, 5 (1998), 1657-1703.

[31] Stoll, H.. "The Supply of Dealer Services in Securities Markets." *Journal of Finance*, 33 (1978), 1133-1151.

[32] Vitale, P.. "Two months in the life of several gilt-edged market makers on the London Stock Exchange." *Journal of International Financial Markets, Institutions and Money*, 8 (1998), 413–432.

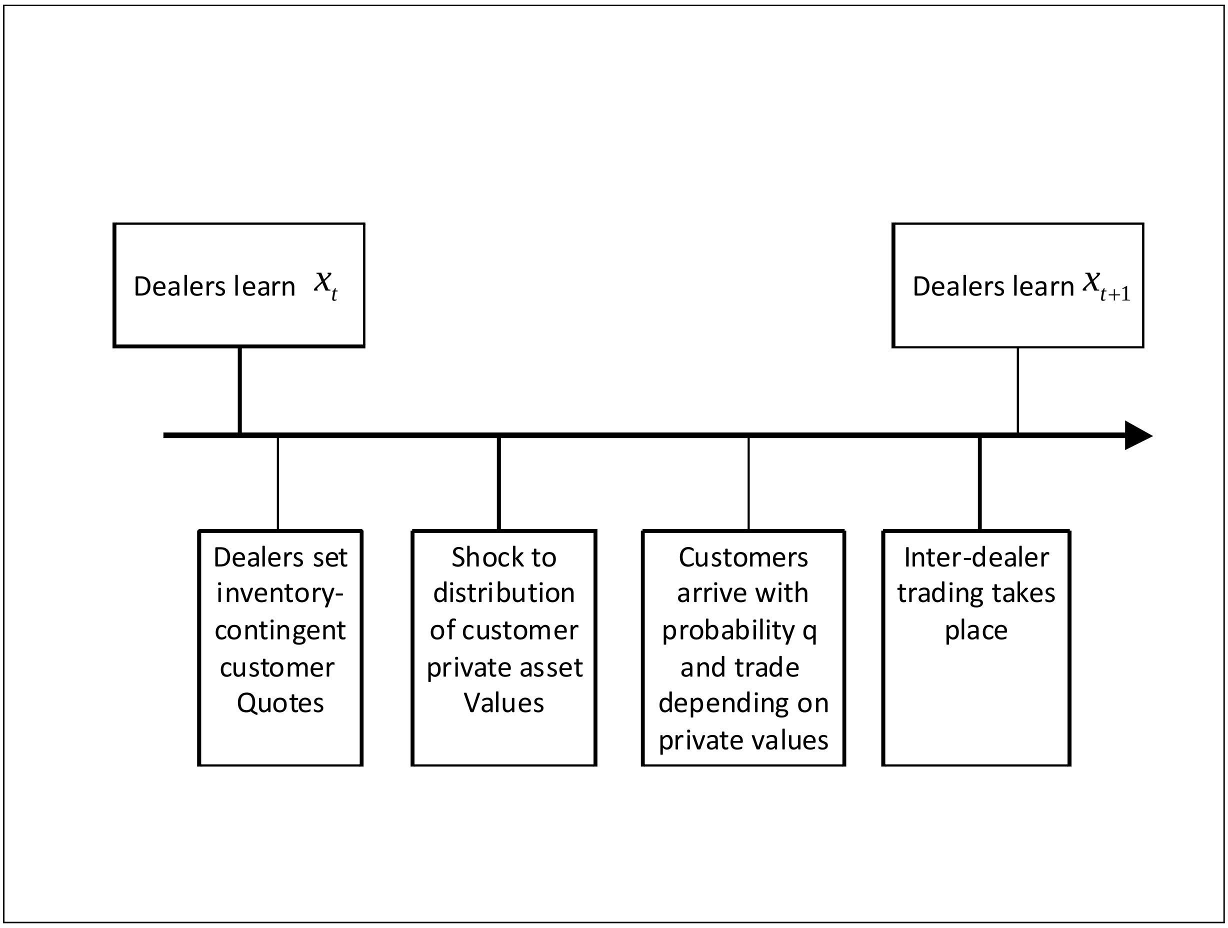

Figure 1: Time line for trading process

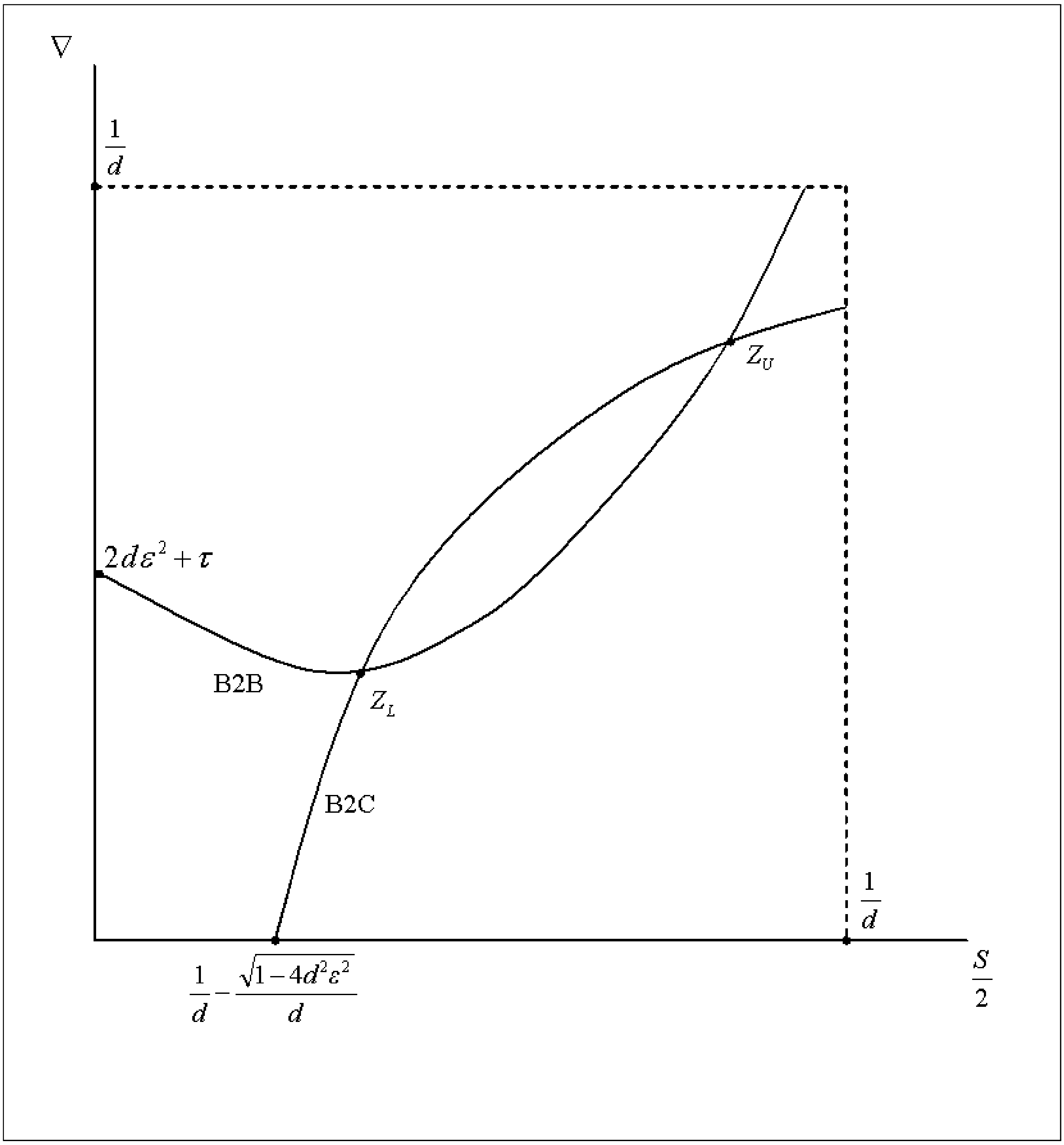

Figure 2: The B2C schedule characterizes the inventory concavity parameter ∇ for optimal B2C quotes under any B2B spread S. The B2B schedule defines the competitive B2B spread S for dealers who have ∇ as their inventory concavity parameter. The two intersections fulfill the equilibrium conditions in both the B2B and B2C market. Of the two equilibria, only one, Z_L, is stable.

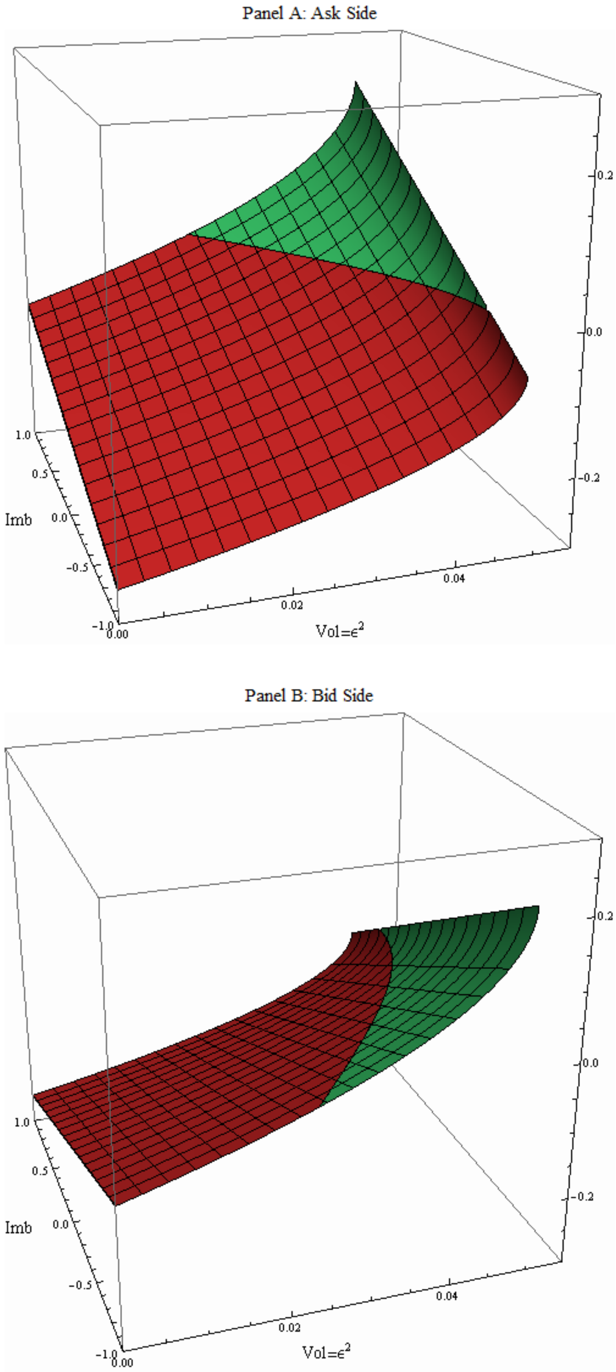

Figure 3: For the ask side (panel A) and the bid side (panel B) we plot vertically the average cross-market spread as a function of volatility (ϵ^2) and the aggregate inventory imbalance (Imb). The red area marks the region for which the average B2C spread is more favorable than the B2B spread. The order 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: European Sovereign Bond Market by Country and MTS Sample Size

The size of the European government bond market in terms of bond value outstanding is described by country for 2005. Only government bonds with a maturity above 1.5 years are considered. The MTS data sample of the B2B market extends over the last three quarters of 2005. The coverage ratio reports the ratio of MTS trading volume divided by the value outstanding in each market. For the Italian market the coverage ratio corresponds to a 100 percent market share since MTS benefits from a legal monopoly in B2B trading. Assuming that the volume to value ratio for Italy applies to all countries, we estimate the percentage market share of MTS in each country (with 100 percent as the upper boundary). Transaction volumes are stated in billions of Euros. European sovereign bonds with a maturity of less than 1.5 years amount to an additional 800 billion Euros.

	European Sovereign Bonds (2005)	MTS Sample of B2B Market (2005q2 to 2005q4)			Coverage Ratios	
Country	Value Outstanding	Bonds	Volume	Trades	Volume/Value	MTS Market Share
Austria	121.9	14	27.28	2,903	0.223	34.6
Belgium	250.9	19	103.16	10,649	0.411	63.6
France	780.9	60	114.82	14,285	0.147	22.8
Germany	603.1	65	125.19	17,141	0.208	32.1
Greece	148.7	22	101.30	12,127	0.681	100.0
Ireland	31.3	5	10.39	1177	0.332	51.4
Italy	990.5	72	640.07	105,465	0.646	100.0
Netherlands	200.4	24	47.41	3,767	0.237	36.6
Portugal	82.7	17	114.39	12,424	1.383	100.0
Spain	286.0	42	85.04	8,727	0.297	46.0
All	3,557.9	340	1,369.05	188,665	0.391	60.8

Table 2: B2B and B2C Trades by Liquidity/Benchmark Status and Bond Maturity

Summary statistics for Italian and non-Italian and inter-dealer (B2B) and customer dealer (B2C) trades executed through MTS are reported in panels A and B, respectively. Bonds are grouped by maturity and liquidity/benchmark status. The MTS sample extends over the last three quarters of 2005 and covers both the B2B and B2C market. Transaction volumes are stated in billions of Euros. The number of bonds included is constrained to be the number of bonds in the B2C market.

Panel A: Italian Sovereign Bonds by Maturity

	MTS Sample of B2B Market (2005q2 to 2005q4)						MTS Sample of B2C Market (2005q2 to 2005q4)							
	All			Benchmark Bonds			All				Benchmark Bonds			
Bond Maturity	Bonds	Volume	Trades	Bonds	Volume	Trades	Bonds	Volume	Trades	Quote Requests	Bonds	Volume	Trades	Quote Requests
Short-Medium	46	368.25	62,453	15	255.26	38,062	46	95.22	19,057	24,604	15	29.56	6,541	8,953
Long	15	217.92	31,012	8	217.92	31,012	15	11.68	4,837	8,425	8	11.68	4,837	8,425
Very Long	11	53.90	12,000	5	39.39	8,985	11	7.24	4,351	7,922	5	5.63	2,562	4,596
All	72	640.07	105,469	28	512.57	78,059	72	114.14	28,245	40,951	28	46.87	13,940	21,974

Panel B: Non-Italian Sovereign Bonds by Maturity

	MTS Sample of B2B Market (2005q2 to 2005q4)						MTS Sample of B2C Market (2005q2 to 2005q4)							
	All			Benchmark Bonds			All				Benchmark Bonds			
Bond Maturity	Bonds	Volume	Trades	Bonds	Volume	Trades	Bonds	Volume	Trades	Quote Requests	Bonds	Volume	Trades	Quote Requests
Short-Medium	153	386.29	42,169	59	286.88	31,534	153	78.65	9,125	11,851	59	47.99	5,688	7,550
Long	75	280.91	30,038	61	268.71	29,068	75	35.22	5,550	9,190	61	35.01	5,471	9,054
Very Long	40	61.78	11,106	23	53.27	9,561	40	12.21	2,584	3,540	23	10.23	2,097	2,867
All	268	728.98	83,313	143	608.86	70,163	268	126.08	17,259	24,581	143	93.23	13,256	19,471

Table 3: Cross-Market Spreads and B2B Spreads by Liquidity

The average of the cross-market spread within each quantile, and overall, is shown for 72 Italian and 268 non-Italian European sovereign bonds of high (benchmark) and low (non-benchmark) liquidity. Panel A reports average spreads for transactions at the ask quotes while Panel B reports spreads for bid transactions. 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). Alongside the cross-market spread we also report the averages of the B2B spreads for the corresponding maturity categories measured (relative to the mid-price $MidP$ between the best B2B ask and bid) at the same moment in time when the B2C transactions occur. Measures of the cross-market spread and the B2B spread are given in cents. At par, these amount to basis points.

Panel A: Ask-Side Spreads

Cross-Market Ask Spread $A - a$

		Italian Bonds		Non-Italian Bonds		
Quantile Means	Quality	Bench.	Non-Bench.	Bench.	Non-Bench.	All
Mean of $Q(1)$	Best	3.82	5.90	5.58	5.22	4.80
Mean of $Q(2)$		1.56	1.44	2.00	2.00	1.93
Mean of $Q(3)$		1.00	0.91	1.37	1.28	1.00
Mean of $Q(4)$	Worst	0.45	0.20	0.01	0.35	0.24
Overall Mean		1.71	2.11	2.24	2.21	1.99

B2B Ask Spreads $A - MidP$

		Italian Bonds		Non-Italian Bonds		
Quantile Means	Quality	Bench.	Non-Bench.	Bench.	Non-Bench.	All
Mean of $Q(1)$	Best	0.64	0.24	0.90	0.89	0.70
Mean of $Q(2)$		1.00	0.62	1.38	1.16	1.04
Mean of $Q(3)$		1.29	1.20	1.66	1.50	1.52
Mean of $Q(4)$	Worst	3.86	5.93	5.10	4.88	4.64
Overall Mean		1.70	1.99	2.26	2.11	1.98

Panel B: Bid-Side Spreads

Cross-Market Bid Spreads $b - B$

		Italian Bonds		Non-Italian Bonds		
Quantile Means		Bench.	Non-Bench.	Bench.	Non-Bench.	All
Mean of $Q(1)$	Best	3.13	6.42	5.26	4.27	4.75
Mean of $Q(2)$		1.00	3.23	1.19	1.00	1.16
Mean of $Q(3)$		0.00	1.14	0.72	0.65	0.43
Mean of $Q(4)$	Worst	−0.22	−0.32	−0.56	−0.59	−0.38
Overall Mean		0.98	2.62	1.65	1.33	1.49

B2B Bid Spreads $MidP - B$

		Italian Bonds		Non-Italian Bonds		
Quantile Means		Bench.	Non-Bench.	Bench.	Non-Bench.	All
Mean of $Q(1)$	Best	0.67	0.60	0.91	0.89	0.76
Mean of $Q(2)$		1.00	2.84	1.40	1.16	1.17
Mean of $Q(3)$		1.46	5.43	1.69	1.50	1.74
Mean of $Q(4)$	Worst	4.14	7.13	5.17	4.68	5.66
Overall Mean		1.82	4.00	2.29	2.06	2.33

Table 4: Cross-Market Spreads and B2B Spreads by Bond Maturity

The average of the cross-market spread within each quantile, and overall, is shown for each of the three main maturity categories of all 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 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). Alongside the cross-market spread we also report the averages of the B2B spreads for the corresponding maturity categories measured (relative to the mid-price $MidP$ between the best B2B ask and bid) at the same moment in time when the B2C transactions occur. Measures of the cross-market spread and the B2B spread are given in cents. At par, these amount to basis points.

Panel A: Ask-Side Spreads

Cross-Market Ask Spread $A-a$						B2B Ask Spreads $A-MidP$					
		Bond Maturity						Bond Maturity			
Quantile Means	Quality	Short-Medium	Long	Very Long	All	Quantile Means	Quality	Short-Medium	Long	Very Long	All
Mean of $Q(1)$	Best	2.21	3.26	9.40	4.64	Mean of $Q(1)$	Best	0.52	0.96	2.53	0.76
Mean of $Q(2)$		1.16	2.00	5.20	1.94	Mean of $Q(2)$		0.99	1.39	4.68	1.06
Mean of $Q(3)$		1.00	1.17	3.35	1.00	Mean of $Q(3)$		1.00	1.50	6.02	1.53
Mean of $Q(4)$	Worst	0.46	0.39	-0.19	0.24	Mean of $Q(4)$	Worst	1.54	2.23	8.28	4.48
Overall Mean		1.21	1.71	4.44	1.95	Overall Mean		1.01	1.52	5.38	1.96

Panel B: Bid-Side Spreads

Cross-Market Bid Spreads $b-B$						B2B Bid Spreads $MidP-B$					
		Bond Maturity						Bond Maturity			
Quantile Means		Short-Medium	Long	Very Long	All	Quantile Means		Short-Medium	Long	Very Long	All
Mean of $Q(1)$	Best	1.23	2.51	9.10	4.17	Mean of $Q(1)$	Best	0.49	0.95	2.25	0.78
Mean of $Q(2)$		0.54	1.00	4.10	1.00	Mean of $Q(2)$		0.97	1.36	4.33	1.14
Mean of $Q(3)$		0.00	0.46	2.36	0.32	Mean of $Q(3)$		1.00	1.50	5.72	1.61
Mean of $Q(4)$	Worst	−0.25	−0.36	−0.11	−0.37	Mean of $Q(4)$	Worst	1.51	2.37	8.18	4.60
Overall Mean		0.38	0.90	3.86	1.28	Overall Mean		0.99	1.55	5.12	2.03

Table 5: 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 the cross-market spread and the B2B spread respectively for ask-side and bid-side B2C activity. 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. 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. 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 ask-side results are presented in Panel A and the bid-side results are presented in Panel B. 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 tests for equality of the constants for competition/no-competition in regressions (1) to (4) is not decisively rejected for the ask-side but is easily rejected on the bid-Side. The F-test statistics (significance) are as follows. Ask-Side(Regression 1): 1.97 (0.14), Ask-Side(Regression 2): 1.84 (0.16), Ask-side(Regression 3): 1.77 (0.17), Ask-Side(Regression 4): 1.81 (0.16), Bid-Side(Regression 1): 3.21 (0.04), Bid-Side(Regression 2): 2.64 (0.07), Bid-Side(Regression 3): 7.61 (0.00), Bid-Side(Regression 4): 6.82 (0.001). Regressions (5) to (8) refer to the B2B bid-ask spread. In these regressions there is no role for the competition dummies and the NO COMP coefficient is simply the regression constant.

Panel A: Ask-Side Spreads

	Cross-Market Spread				B2B Spread			
	Full Sample		Long Bonds		Full Sample		Long Bonds	
Regression	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NO COMP	0.423	0.436	0.974	0.518	−0.023	−0.025	−0.919	−0.879
T-Stat	2.355	2.457	2.075	1.144	−0.099	−0.104	−1.499	−1.454
COMP 2+	0.576	0.584	1.577	1.092				
T-Stat	3.348	3.444	3.627	2.599				
Log B2C Quantity	−0.067	−0.33	−0.11	−0.113				
T-Stat	−7.012	−11.847	−4.929	−5.169				
Log Realized Volatility	0.01	0.013	−0.085	−0.06	0.277	0.277	0.408	0.406
T-Stat	0.24	0.305	−0.918	−0.667	4.719	4.714	3.130	3.126
Imbalances, Imb		0.328		0.477		−0.037		−0.040
T-Stat		11.79		8.724		−1.316		−0.820
Obs	5159	5159	1561	1561	5159	5159	1561	1561
OLS RBar-Squared	0.561	0.570	0.061	0.096	0.829	0.829	0.446	0.445

Panel B: Bid-Side Spreads

	Cross-Market Spread				B2B Spread			
	Full Sample		Long Bonds		Full Sample		Long Bonds	
Regression	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NO COMP	−0.469	−0.425	0.921	0.878	−1.011	−1.015	2.317	2.319
T-Stat	−2.105	−1.904	2.462	2.386	−3.673	−3.684	5.628	5.642
COMP	−0.468	−0.406	0.641	0.637				
T-Stat	−2.2	−1.907	1.972	1.969				
Log B2C Quantity	−0.063	−0.059	−0.074	−0.073				
T-Stat	−5.47	−5.18	−3.565	−3.529				
Log Realized Volatility	0.15	0.143	0.122	0.119	0.554	0.555	0.590	0.590
T-Stat	2.764	2.638	1.568	1.535	8.020	8.026	5.536	5.547
Imbalances, Imb		−0.313		−0.345		0.019		0.074
T-Stat		−9.757		-7.545		0.537		1.763
Obs	4441	4441	2082	2082	4441	4441	2082	2082
OLS RBar-Squared	0.512	0.519	0.071	0.091	0.817	0.817	0.434	0.434