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Fragmentation and Strategic Market-Making

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Abstract

How does trading in one venue affect the quoting strategies of market makers in other venues? We develop a two-venue imperfect competition model in which market makers face quadratic costs when absorbing shocks. Nonconstant marginal costs imply that absorbing a shock in one venue simultaneously changes marginal costs in all other venues. Moreover, market makers strategically choose which shock(s) to absorb. These two forces may intensify competition, leading to enhanced liquidity. Using Euronext proprietary data, we track individual best bid and ask quotes of intermediaries in each venue. We uncover evidence of strategic cross-venue market-making behavior which is uniquely predicted by our model.

I. Introduction

Today's financial markets are more fragmented than ever, multiplying the possibilities of cross-market strategies (Menkveld (2013)). Arbitrage strategies, duplicate strategies, or directional trading strategies are mechanisms that explain connectedness between venues (e.g., ESMA (2016)).

The present article explores a new and additional channel by which venues are interconnected: strategic behavior resulting from cross-market inventory cost linkages. In our setting, market-making intermediaries trade in multiple venues and face quadratic costs for supplying liquidity in the risky asset held in inventory.

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Due to nonconstant marginal costs, absorbing a shock in one venue simultaneously changes market maker's marginal costs in all other venues. Anticipating the change in inventory due to the trade in one venue, a market maker strategically updates her quoting aggressiveness in all other venues. Remarkably, this change in marginal costs has an impact on the quoting strategies of competitors, thereby affecting the degree of intensity of competition between market makers, and, in turn, the liquidity in any venue. We develop this intuition in a two-venue duopoly model and show that fragmentation may lead to more competition and more liquidity. We test this new result using a proprietary message and trade data set from Euronext on multitraded stocks, in which we can uniquely identify financial institutions.

Our modeling framework considers 2 risk-averse market makers who differ by their inventory position (referred to inventory divergence), or, equivalently, by their costs of providing immediacy. The market maker with the more divergent inventory position produces immediacy at a smaller cost.

Market makers compete to post prices for the same asset traded on two transparent venues. We assume that the venue referred to as the dominant market receives a larger shock than the alternative venue referred to as the satellite market.[1] The two venues may be simultaneously hit by exogenous liquidity shocks, which might be of the same sign or of opposite signs. When shocks have the same sign, the cross-market cost linkage exerts a negative force on quotes. A market maker ready to absorb a shock in a venue anticipates that her cost to simultaneously provide same-side immediacy increases in the other venue. This effect reverses when shocks have opposite signs.

Multiple venues generate another channel for strategic behavior: the possibility to choose which shock to absorb, and thus the venue on which to compete. This feature affects market makers in distinct ways. The market maker with the smaller cost can choose to absorb both shocks, if her cost is small enough; otherwise, she chooses to absorb the shock with the most favorable impact on her inventory exposure. The second market maker, with a less divergent inventory, is not able to undercut simultaneously in both venues and hence never trades in both. He keeps, however, the freedom to compete in any of the two venues, endogenously affecting the optimal pricing of his opponent.

These two features interact to generate two alternative situations. The first situation consists of a "low competition" case in which the cost of the more divergent market maker, even if smaller, is too high to profitably absorb two shocks. She chooses to absorb the shock in the dominant venue while letting her opponent provide immediacy in the satellite venue. Each market maker behaves as a local monopolist by pricing high. The second situation corresponds to an "intense competition" case in which the inventory cost of the more divergent market maker is small enough to let her absorb all shocks. The intensity of price competition, however, varies with the sign of the shock. Interestingly, we show that there exists an "ultracompetitive" case when shocks have the same sign, in which the more

[1]This two-venue environment particularly fits Australian, Canadian, or European equity markets in which the incumbent exchange still has a strong presence in its domestic market.

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divergent market maker prices are low in each venue in order to undercut and avoid being undercut, and absorb all inventory-reducing shocks.

Strategic market-making influences liquidity. We find that a fragmented market may be more liquid than a centralized batch market, mainly due to the ultracompetitive case. We also show that the cross-market cost linkage makes liquidity of the venues interconnected even if liquidity demands are exogenously specified, adding a new explanation for commonality in liquidity. Our model abstracts, however, from some important complexities of market organization, and therefore does not allow performing any normative analysis of the policy implications of fragmentation.

We test the predictions of our model using a proprietary data set from Euronext on multitraded stocks over a 4-month period in 2007. This setting has three advantages. First, trading rules in all these markets (Amsterdam, Brussels, Paris, and Lisbon) are harmonized, with identical but separate limit order books. We can therefore focus on the effect of fragmentation on price competition without potential confounding effects (caused by different tick sizes, trading fees, speeds, or degrees of transparency). Second, during that period, Euronext attracted the overwhelming majority of the trades (up to 98%), allowing us to trace any changes in members' inventory. Third, our data set contains a unique identifier for each participant in all venues, enabling us to track members' trades and messages from one venue to another. In particular, we build the individual best bid (highest alive buy limit order) and best ask (lowest alive sell limit order) at any second in any venue of 30 multivenue intermediaries, among which 6 are designated market makers (DMMs) with a Euronext market-making agreement. To the best of our knowledge, our article is the first article to trace best bid and ask quotes posted by intermediaries in a venue.

To establish the external validity of our model, we investigate how intermediaries revise quotes in one venue following a trade in another venue. We also analyze the quoting reaction of the competitors after that trade. To perform these tests, we build a measure of quoting aggressiveness, which is the distance between each trader's bid (or ask) quote relative to the best market bid (or ask) quote at any time t. This measure dynamically controls for any changes in fundamental information, because changes in fundamental value are incorporated in both the intermediaries' quotes and market prices, and are therefore netted out. This feature makes sure that inventory management concerns are the main driving force of our results. We find that DMMs significantly decrease their cross-market quoting aggressiveness by 0.6 basis points (bps) following a trade on that side. A decrease by 1 standard deviation in quoting aggressiveness of the executing DMM decreases the quoting aggressiveness of competitors by 0.22 bps on the bid side and 0.34 bps on the ask side.

Last, we provide evidence for the existence of "ultracompetitive" effects, which are specific to our model. First, we find that intermediaries with highly divergent inventories behave more aggressively when order flows have the same sign across venues. Second, our empirical analysis shows that bid–ask spreads decrease when competition heats up. All these results support our imperfect competition model.

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Our analysis is related to a number of articles analyzing linkages between venues (see, e.g., Foucault and Menkveld (2008), O'Hara and Ye (2011), van Kervel (2015), or Chen and Duffie (2021)). Although these articles assume that quotes are set by competitive market makers, our model shows that the best response of strategic market makers with nonconstant marginal costs may lead to more competition and lower spreads. Our model offers a new and alternative mechanism linking venues, while being consistent with empirical results uncovering positive effects of market fragmentation on liquidity.

This article is organized as follows: Section II presents the model. Section III describes data and tests the main implications of the model. Section IV concludes the article. All proofs are available in the Supplementary Material.

II. The Model

A. The Basic Setting

We consider the market for a risky asset with a random final cash flow $\widetilde{v}$ normally distributed with expected value μ and variance σ^2. There are two types of market participants: investors who demand liquidity and market makers who supply liquidity. The trading game consists of four stages, as follows:

Stage 1: Reservation prices and costs of supplying liquidity. Liquidity is supplied by two equally risk-averse intermediaries with coefficient ρ.[2] At Stage 1, market maker i receives a nonzero inventory position in the risky asset I_i, where I_i is the realization of the random variable $\widetilde{I}_i$ uniformly distributed on $[I_d, I_u]$ $(i=1,2)$.[3] We denote r_i the minimum selling (resp. maximum buying) price at which market makers can execute buy orders (resp. sell orders) without incurring losses. The reservation price r_i is defined by equating expected utility functions $\text{EU}(Q, r_i) = \text{EU}(0, r_i)$, where $U(Q, r_i)$ is the Constant Absolute Risk Aversion (CARA) utility of market maker i absorbing the demand shock Q at price r_i, that is,

$$r(Q; I_i) \equiv r_i(Q) = \mu - \rho\sigma^2 I_i + \frac{\rho\sigma^2}{2} Q. \tag{1}$$

Because of nonzero inventory, market makers are willing to trade to reduce inventory risk. Equation (1) shows that longer market makers with lower reservation prices are induced to post lower bid and ask prices to attract buy orders and reduce their inventory exposure. However, the last term shows that the larger the shock Q to be absorbed, the higher the quote a market maker would post, making her less likely to attract buy orders.

Reservation prices may be interpreted as costs for providing immediacy, which allows us to define (total) inventory costs for market maker i by $\text{TC}_i(Q) = r_i(Q) \times Q$ $(i=1,2)$. Inventory costs are quadratic, and marginal costs are nonconstant.[4] Large transactions are more risky and thus more costly as they may lead to

[2] We use "market maker" and "intermediary" interchangeably.

[3] All random variables are independent.

[4] This assumption is common in the theoretical literature (see, e.g., Ho and Stoll (1983), Biais, Foucault, and Salanié (1998), or Garleanu and Pedersen (2013)).

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more unbalanced inventory positions. For ease of exposition, we assume that market maker 1 is endowed with a longer inventory position, that is, $I_1 > I_2$. This assumption implies that the costs of absorbing the shock Q are smaller for market maker 1: $\mathrm{TC}_1(Q) < \mathrm{TC}_2(Q)$.

Stage 2: Market fragmentation. The risky security trades in 2 trading venues, denoted by D and S, that we assume are transparent. At Stage 2, a venue m can be exogenously hit by a liquidity shock with probability ζ_m ($m = D$, or S).[5] We assume that $\zeta_D > \zeta_S$ and that the liquidity demand sent to venue D, denoted by Q_D, is greater in magnitude than that routed to venue S, that is, $|Q_D| > |Q_S|$. We call venue D the dominant market, and venue S the satellite market. By convention, a positive (negative) shock generates a buy (sell) liquidity demand denoted by $Q_m > 0$ (resp. $Q_m < 0$), $m = D$, or S. We denote by ζ the probability that both venues are simultaneously hit by shocks ($\zeta = \zeta_D \times \zeta_S$), and by γ the probability that the shocks have the same sign in the different venues.

For brevity, we focus on the case in which shocks generate a net-buying order flow, that is, $Q_D + Q_S > 0$, or, equivalently, $Q_D > 0$, while Q_S might be a buying or selling liquidity demand. Symmetric results are easily obtained for a net-selling order flow. Note that, since the total order flow is net-buying ($Q_D + Q_S > 0$), market maker 1 benefits from a competitive advantage (given that we assume $I_1 > I_2$).

Stage 3: Quoting strategies. We assume that intermediaries behave strategically and have access to all trading venues at the same time. At Stage 3, conditional on observing Q_D and Q_S, multivenue market makers post *simultaneously* their quotes in venues D and S. The market maker who posts the lowest ask price (highest bid price) in venue m executes $Q_m > 0$ ($Q_m < 0$), for $m = D, S$.

A multivenue quoting strategy for market maker i is a pair of quoted prices $\left(p_i^D, p_i^S\right)$, where p_i^D is the price posted by market maker i in venue D and p_i^S is the price posted by i in venue S (which is an ask price if $Q_m > 0$ or a bid price if $Q_m < 0$).[6]

In our model, we need to consider under what conditions a market maker who competes in one venue decides to compete in an additional venue. Denote by Q_{-m} the liquidity shock in the additional venue, given that the market maker is ready to absorb the shock Q_m in his "home" venue. We introduce a specific reservation price $\widehat{r}_i$, referred to as the "stay-at-home" price, at which market maker i is indifferent to executing the liquidity demand Q_{-m} in addition to the demand Q_m. Specifically, let $\widehat{r}_i(Q_{-m})$ be defined by equating $\mathrm{EU}(Q_{-m} + Q_m, \widehat{r}_i) = \mathrm{EU}(Q_m, \widehat{r}_i)$. It follows that

$$\text{(2)} \qquad \widehat{r}_i(Q_{-m}) = \mu - \rho\sigma^2 I_i + \frac{\rho\sigma^2}{2} Q_{-m} + \rho\sigma^2 Q_m = r_i(Q_{-m}) + \rho\sigma^2 Q_m.$$

The "stay-at-home" price may be rewritten as $\widehat{r}_i(Q_{-m}) = r(Q_{-m}; I_i - Q_m)$. Market maker i behaves as if she is sure to execute (inelastic) orders in venue m

[5] The baseline model assumes that the order flow exogenously fragments across venues. In Section 2.B in the Supplementary Material, we address the case of endogenous fragmentation by assuming that a global liquidity demander has access to all venues and minimizes his trading costs by optimally splitting orders between venues. We show that, even in this case, the liquidity demander optimally chooses to split orders, leading to a fragmented market.

[6] Market makers' trading profits are detailed in Section 1.A in the Supplementary Material.

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(consistent with a monopolistic situation) and, anticipating the impact of Q_m on her inventory $(I_i - Q_m)$, her true value for accepting entering in the other venue $-m$ is now this new reservation price, $\widehat{r}_i(Q_{-m})$. For example, if $Q_m > 0$, any selling price below $\widehat{r}_i$ is insufficiently high for the market maker to try to capture the orders Q_{-m}. She prefers not to compete in the additional venue. Notice that $\widehat{r}_i(Q_{-m}) > r_i(Q_m + Q_{-m})$ if $Q_m > 0$ and $\widehat{r}_i(Q_{-m}) \leq r_i(Q_m + Q_{-m})$ if $Q_m \leq 0$.

Stage 4: End. The cash flow of the risky asset is realized. No uncertainty remains.[7]

B. Equilibrium Quotes in a Fragmented Market

This section analyzes the Nash equilibria of the quoting game. Let us first consider a centralized market in which liquidity demands are batched and sent to a unique venue, as in Ho and Stoll (1983). In this case, the market maker with a longer inventory position (market maker 1 by assumption) posts a more competitive ask price, by slightly undercutting the reservation price of her shorter opponent: $\left(a_1^c\right)^* = r_2(Q_D + Q_S) - \varepsilon$, where ε is an arbitrarily small positive number.[8] The longer intermediary behaves strategically by shading her ask price upward, that is, she chooses to post an ask price above her reservation price $(r_1(Q_D + Q_S))$ to increase her payoff, but still below the true value of her opponent.

1. Preliminary Results

When markets are fragmented, market makers strategically compete in more than one venue. As a consequence, they might strategically choose to withdraw from some venues to compete more intensely in others. In a two-venue setting, Lemma 1 shows that at equilibrium (if it exists), two different situations emerge: either a single market maker virtually consolidates the market by executing orders in all venues, or each market maker specializes in one venue, by trading only the order from that venue.

Lemma 1. Assume that $I_1 > I_2$ and that $Q_D + Q_S > 0$. If an equilibrium exists, then:

1. If inventory costs are such that $\mathrm{TC}_1(Q_D + Q_S) < \mathrm{TC}_1(Q_D) + \mathrm{TC}_2(Q_S)$ or, equivalently, $(I_1 - I_2 - Q_D)Q_S > 0$, then a market maker consolidates the market through a multivenue execution. Conversely, if $\mathrm{TC}_1(Q_D + Q_S) \geq \mathrm{TC}_1(Q_D) + \mathrm{TC}_2(Q_S)$ or, equivalently, $(I_1 - I_2 - Q_D)Q_S \leq 0$, then orders sent to different venues are executed by different market makers.
2. If there exists an equilibrium such that a market maker consolidates the market, then the longer market maker executes all orders. If there exists an equilibrium such that each market maker specializes in one venue, then the longer market maker executes the buy demand sent to the dominant venue, whereas the shorter intermediary executes orders sent to the satellite venue.

Recall that in a centralized market, orders are batched and crossed (if $Q_S < 0$) and the outcome depends only on the divergence between market makers'

[7]The extensive form of the trading game is given in Figure IA.1 in the Supplementary Material.

[8]ε is such that $\left(a_1^c\right)^*$ equals the reservation price of the opponent rounded down to the nearest tick.

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inventories ($I_1 - I_2$) because this determines who has the lowest cost of supplying liquidity. In a two-venue setting, the problem is more complex. First, in order to decide which shock(s) to absorb, market makers have to consider the different costs to supply liquidity in each venue, $\mathrm{TC}_i(Q_m)$, and also in both venues, $\mathrm{TC}_i(Q_m + Q_{-m})$.

Second, Lemma 1 indicates that there exist cases in which market maker 1 behaves as if capacity-constrained. Even if market maker 1 has the smallest cost of producing liquidity, this cost may be too high to profitably absorb all shocks, as indicated by the inequality $\mathrm{TC}_1(Q_D + Q_S) \geq \mathrm{TC}_1(Q_D) + \mathrm{TC}_2(Q_S)$.[9] In that case, market maker 1 only executes orders in the venue with the most favorable impact on her inventory risk, that is, venue D. For instance, consider the case in which the divergence in inventories is high, that is, $I_1 - I_2 - Q_D \geq 0$, and the shock hitting S is negative ($Q_S < 0$). Since market maker 1's inventory is very long and risky, she is willing to execute all incoming *buy* orders to lay off her inventory. Hence, she trades only Q_D. Executing sell orders in S would indeed aggravate her inventory exposure. In a two-venue setting, there is the possibility to compete in only one venue, which, in turn, influences market-making strategies.

Third, each market maker's inventory position is aggregated across venues. This "global" inventory position makes market makers' costs of supplying liquidity interdependent between venues. The marginal cost of supplying liquidity in venue m depends on the *output* in venue $-m$: $\frac{\partial \mathrm{TC}_i(Q_m + Q_{-m})}{\partial Q_m} = \frac{\partial \mathrm{TC}_i(Q_m)}{\partial Q_m} + \rho\sigma^2 Q_{-m}$. The second term, $\rho\sigma^2 Q_{-m}$, is a new cross-market effect, absent from any competition in a unique centralized venue. If market maker i chooses to absorb a buy (sell) demand in venue $-m$, her cost of providing liquidity in m increases (decreases), which influences her willingness to post competitive quotes in m. The cross-market cost linkage created by the existence of a second venue affects competition either way: negatively when the shocks hitting venues have the same sign, or positively when they have opposite signs. The negative vs. positive effect of the cross-market cost linkage on price competition is caused by both nonconstant marginal costs of supplying liquidity and the strategic behavior of the market makers.[10]

2. Optimal Quotes

Proposition 1. Assume that $I_1 > I_2$ and $Q_D + Q_S > 0$.

1. If $(I_1 - I_2 - Q_D)Q_S > 0$, there exists a Nash equilibrium, in which market maker 1 consolidates the market by posting the best prices in all venues. At equilibrium,

$$\begin{cases} \left(\left(a_1^D\right)^*, \ \left(a_1^S\right)^*\right) = \left(r_2(Q_D) - \varepsilon, \ r_2(Q_S) - \varepsilon\right), & \textit{if } Q_S > 0, \\ \left(\left(a_1^D\right)^*, \ \left(b_1^S\right)^*\right) = \left(\hat{r}_2(Q_D) - \varepsilon, \ r_2(Q_S) + \varepsilon\right), & \textit{if } Q_S < 0. \end{cases} \tag{3}$$

[9] In our model, inventory plays the role of a "soft" capacity constraint (Cabon-Dhersin and Drouhin (2020)).

[10] With constant marginal costs, there is no cross-market effect.

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2. If $(I_1 - I_2 - Q_D)Q_S \leq 0$, there exists a unique Nash equilibrium, in which market maker 1 posts the best selling price in the dominant market, whereas market maker 2 posts the best price in the satellite market:

$$(4)\quad \begin{cases} \left(\left(a_1^D\right)^*,\ \left(a_2^S\right)^*\right) = \left(\widehat{r}_2(Q_D) - \rho\sigma^2 Q_S \times \eta - \varepsilon,\ \widehat{r}_1(Q_S) - \varepsilon\right), & \textit{if } Q_S > 0, \\ \left(\left(a_1^D\right)^*,\ \left(b_2^S\right)^*\right) = \left(\widehat{r}_2(Q_D) - \varepsilon,\ \widehat{r}_1(Q_S) + \varepsilon\right), & \textit{if } Q_S < 0, \end{cases}$$

where ε is a small positive number and η equals $(I_1 - I_2)/Q_D \in]0,1]$.

There are two driving forces specific to our two-market duopoly: i) the possibility of choosing the venue on which to compete and ii) a cross-market cost linkage due to the global management of the position across venues. The net effect of these forces creates two opposite situations in our model: i) an "intense competition" case in which the costs of supplying liquidity are small enough to allow market maker 1 to price low in the two venues in order to undercut and avoid being undercut ($\text{TC}_1(Q_D + Q_S) < \text{TC}_1(Q_D) + \text{TC}_2(Q_S)$) and ii) a "low competition" case in which market maker 1 cannot absorb shocks in the two venues and prices high to maximize profit in one venue, whereas market maker 2 chooses the other venue ($\text{TC}_1(Q_D + Q_S) \geq \text{TC}_1(Q_D) + \text{TC}_2(Q_S)$).

As an illustration, we provide a numerical example. Figure 1 shows the best prices as a function of the divergence in inventories $(I_1 - I_2 - Q_D)$, both for a fragmented market and a centralized one. Graph A illustrates the case in which two positive shocks simultaneously hit venues D and S. Graph B illustrates the case of shocks of opposite signs. In both cases, the y-axis separates the region in which competition is intense from the region in which competition is low. There are four regions in the figure, denoted A (divided into A1 and A2), B, C, and D.

First, consider the case of "intense competition," in which market maker 1's inventory costs are small enough to provide liquidity in the two venues, that is, $(I_1 - I_2 - Q_D) \times Q_S > 0$ (regions B and C in Figure 1).

• **Suppose that $Q_S > 0$ (region B).** Shocks that hit venues D and S have the same sign. Due to the negative impact of the cross-market cost linkage, the costs of providing liquidity are higher in both venues. However, in this region, market maker 1 is very long ($I_1 - I_2 - Q_D > 0$) and has incentives to undercut market maker 2 in both venues. Her opponent, however, might choose to compete in a single venue, D or S. Market maker 1 is thus obliged to quote below the minimum selling price of market maker 2, $r_2(Q_m)$, in each venue m. This competitive pressure offsets the negative impact of the cross-market cost linkage, resulting in "ultracompetitive" prices, that is, prices even more competitive than in a centralized market $\left(\left(\left(a^D\right)^*, \left(a^S\right)^*\right) < \left((a^c)^*, (a^c)^*\right)\right)$.

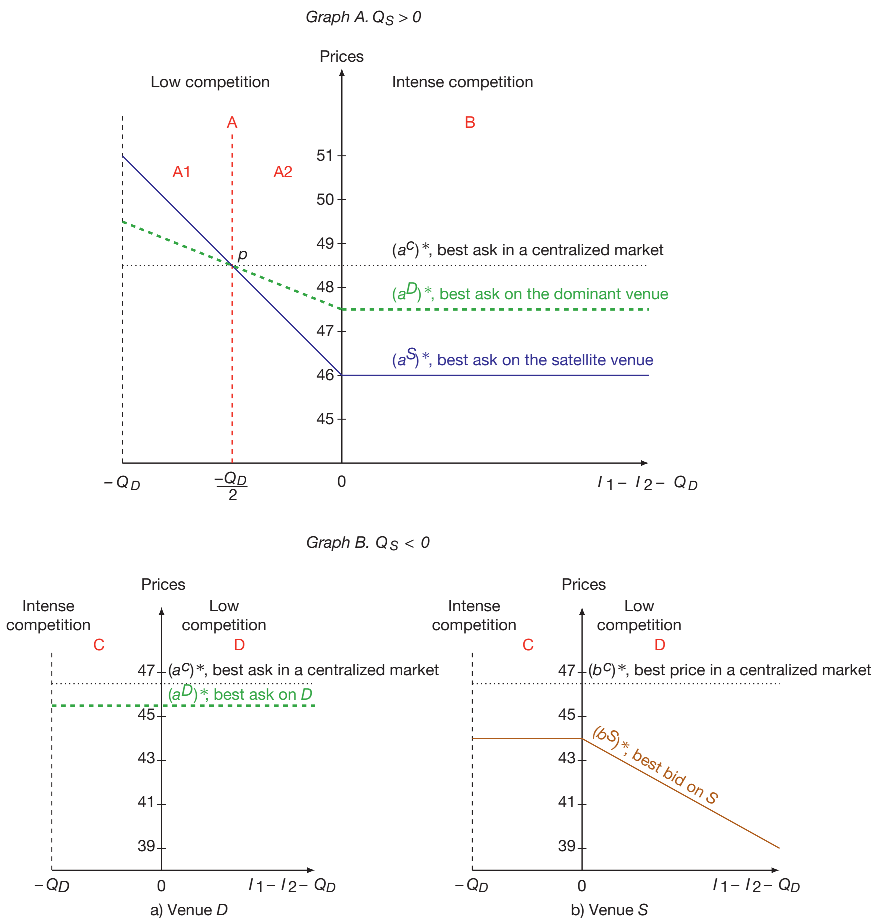
• **Suppose that $Q_S < 0$ (region C).** Market maker 1 is less long ($I_1 - I_2 - Q_D < 0$). By executing buy orders sent to D, she will be shorter than market maker 2, and able to undercut market maker 2's highest possible buying price, $r_2(Q_S)$, in venue S. The cross-market cost linkage plays a positive role as it allows market maker 1 to decrease her selling price in venue D even more, to $\widehat{r}_2(Q_D) < r_2(Q_D)$.

Due to the convexity of inventory costs, supplying liquidity for same-sign shocks is much more costly than for opposite-sign shocks (ceteris paribus), which is

FIGURE 1

Illustration of Proposition 1

Figure 1 illustrates Proposition 1. Graph A shows equilibrium selling prices in a fragmented market when buy shocks hit simultaneously venues D and S. Graph B depicts best prices when a buy shock hits venue D (Graph B(a)) and a sell shock hits venue S (Graph B(b)). The dotted line depicts the best ask price in a centralized market, the dashed green line plots the best selling price in venue D, the plain blue line plots the best ask in venue S (when $Q_S > 0$), and the plain orange line plots the best bid price in venue S (when $Q_S < 0$). In case of two positive shocks, the intersection point of the 3 equilibrium prices ($(a^c)^*$, $(a^D)^*$, and $(a^S)^*$), termed p, is also represented in Graph A. p is such that $I_1 - I_2 = \frac{Q}{2}$. Regions B and C depict "intense competition" cases, whereas regions A1, A2, and D depict "low competition" cases. Parameters are $Q_D = 5{,}000$, $|Q_S| = 2{,}000$, $I_u = 15{,}000$, $I_d = 0$, $\mu = 50$, $\sigma^2 = 0.001$, $\rho = 1$, $I_2 = 5{,}000$, and I_1 is varying.



reflected in the negative or positive role of the cross-market cost linkage. That is the reason why we refer to quotes posted by the longer market maker in region B as "ultracompetitive."

Second, consider the "low competition" case, in which market maker 1's cost of supplying liquidity in both venues is too high, that is, $(I_1 - I_2 - Q_D) \times Q_S \leq 0$ (regions A and D in Figure 1).

- **Suppose that $Q_S > 0$ (region A).** Market maker 1 is less long ($I_1 - I_2 - Q_D \leq 0$). If she is in position to undercut market maker 2 in the dominant venue D, she is not long enough to undercut in venue S ($I_1 - Q_D \leq I_2$). She thus

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chooses to quote her "stay-at-home" price in S, which is anticipated by marker maker 2. To be sure of undercutting and not being undercut in the dominant venue, in which trade is more profitable, market maker 1 must, however, quote a price more aggressive than the "stay-at-home" price of market maker 2, resulting in posting the price $\left(a_1^D\right)^* \leq \widehat{r}_2(Q_D)$. Both the cross-market cost linkage and the possibility of absorbing only orders sent to one's "home" venue play an anticompetitive role, resulting in less aggressive prices.

The equilibrium selling price in the satellite venue might be higher than that of the dominant venue despite there being a smaller quantity to execute. The intuition for this result is as follows: When marker makers' inventories tend to be equal $(I_1 - I_2 \rightarrow 0)$, the longer market maker still executes the larger demand, whereas the shorter market maker executes the smaller demand. A higher equilibrium price in the satellite market compensates, however, market maker 2 for the smaller execution and prevents him from deviating and executing the larger trade. Therefore, there must exist an intersection point p at which the selling prices of both venues are equal, as shown in Figure 1. Region A is divided into A1 and A2 according to the intensity of price competition between venues. In region A1 (resp. A2), price competition is weaker (resp. stronger) and best market prices are less (resp. more) competitive in a fragmented market than those in a centralized market.

• **Suppose now that $Q_S < 0$ (region D).** In this region, market maker 1 is very long $(I_1 - I_1 \geq Q_D)$. Reducing her inventory risk exposure is the primary consideration for the market maker choice of trading venue. She then chooses to compete in venue D and not in venue S. Note that even if she undercuts market maker 2 in venue D, she is still longer than him $(I_1 - Q_D \geq I_2)$ and has no chance to execute sell orders in venue S. Symmetrically, the shorter market maker 2 chooses to compete in venue S, and not in venue D. This creates a situation in which each market maker acts as a local monopolist in their preferred or "home" venue and quotes in the other venue her/his "stay-at-home" price $\widehat{r}_i(Q_{-m})$. Even if the cross-market cost linkage exerts a positive force on inventory costs, this is more than offset by the anticompetitive role played by the possibility of choosing which shock to be absorbed.

C. Assessing Ex Ante Execution Quality

This section analyzes how multivenue market-making strategies affect liquidity. Using the terminology developed in Degryse, de Jong, and van Kervel (2015), we investigate local liquidity by computing the expected (half-)spreads set in each venue, and global liquidity by aggregating the expected transaction costs over the two venues. For ease of exposition, we standardize liquidity shocks and define ϕ_m by $\phi_m = \frac{Q_m}{I_u - I_d}$ if $Q_m > 0$ and $-\phi_m = \frac{Q_m}{I_u - I_d}$ if $Q_m < 0$. Proposition 2 follows.

Proposition 2 (Local liquidity). The expected (half-)spreads in the dominant and the satellite venues are:

$$(5) \quad E\left(s^D\right) = \rho\sigma^2 (I_u - I_d)\left[\left(\frac{1}{2}\phi_D + \frac{1}{6}\right) + \zeta_S \phi_S \left[\gamma\left(\phi_D - \frac{(\phi_D)^2}{3}\right) - (1-\gamma)\right]\right],$$

$$E(s^S) = \rho\sigma^2 (I_u - I_d)\left[\left(\frac{1}{2}\phi_S + \frac{1}{6}\right) + \zeta_D \phi_D \left[\phi_D - \frac{(\phi_D)^2}{3} - (1-\gamma)\right]\right], \tag{6}$$

where ζ_m is the probability that a liquidity shock hits venue m and γ is the probability that shocks hitting venues D and S have the same sign ($m = D, S$).

Local spreads are made of two components. The first one is the *direct* price impact of orders routed to that venue. This corresponds to the expected best offer that would prevail if there were no shock hitting the other venue ($\phi_{-m} > 0$ with probability ζ_{-m}). The second component consists of the *indirect* price impact of trading in the other venue (ϕ_{-m}) resulting from the effect of the cross-market cost linkage, while its magnitude is related to market makers' market power. This component may be positive or negative, depending on γ and ϕ_D. In particular, the local expected spreads adversely enlarge when γ increases. When γ is sufficiently low, the opposite occurs, due to the positive impact of the cross-market cost linkage. Note that the existence of a second venue is asymmetric. The dominant venue has a stronger influence on local spreads set in the satellite venue than the other way round, due to i) the stronger effect of the cross-market cost linkage and ii) the intensity of the competition, which is lower in the satellite market (see regions A1 and D in Figure 1).[11]

Using Proposition 2, Corollary 1 studies total expected trading costs.[12]

Corollary 1 (Global liquidity). Total expected trading costs are lower in a fragmented market than in a centralized market if and only if the probability of having same-sign shocks is greater than $\frac{1}{3}$ and the magnitude of the (standardized) shock is neither too large, nor too small ($\Phi_\gamma^1 < \phi_D < \Phi_\gamma^2$).

The intuition of the corollary is as follows: Figure 1 shows that prices are more competitive in a fragmented market in 2 regions $A2$ and B, which correspond to the case in which shocks have the same sign and the divergence in inventories is not too low. Therefore, global liquidity improves when the probability of having same-sign shocks and the probability of a large divergence in inventories are both sufficiently high. The latter condition depends on ϕ_D, which should not be too large ($\phi_D < \Phi_\gamma^2$) for that condition to be true. When the probability that shocks have opposite signs increases ($\gamma \to 1/3$), global liquidity deteriorates and could be lower than in a centralized market, unless prices remain as competitive as in a centralized market (region C). This case corresponds to a low divergence in inventories, that is, ϕ_D should not be too small ($\Phi_\gamma^1 < \phi_D$) for that second condition to be true.

Proposition 2 and Corollary 1 imply that when shocks' having the same sign are more likely, local liquidity deteriorates but global liquidity improves. The latter

[11]Given that $\zeta_D > \zeta_S$, $\phi_D > \phi_S$, and $(1-\gamma)\left(\phi_D - \frac{(\phi_D)^2}{3}\right) \geq 0)$, we deduce that $\phi_D - \frac{(\phi_D)^2}{3} - (1-\gamma) > \gamma\left(\phi_D - \frac{(\phi_D)^2}{3}\right) - (1-\gamma)$. The indirect impact of a second venue is thus stronger for a satellite venue.

[12]See Section 3.A in the Supplementary Material for an analysis of the effect of fragmentation on transaction costs and for a discussion about the economic forces driving differences between fragmented and centralized markets.

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is due to the intensified competition caused by the possibility of competing fiercely in only one venue. The opposite holds when the probability of having shocks of opposite signs is high.[13]

Local spreads are affected by orders sent to other venues due to multivenue market makers. Our model proposes a new explanation for venue interconnectedness, namely, the strategic placement of their quotes by the market makers in the face of nonconstant marginal costs of supplying liquidity. This explanation is distinct from those found in the literature which focus on arbitrage strategies (Foucault, Kozhan, and Tham (2017)), duplicate strategies (van Kervel (2015)), or directional trading strategies (Baldauf and Mollner (2021)).

Proposition 3 (Interconnected liquidity). The bid–ask spreads of the venues covary jointly, and more strongly when the probability of having same-sign shocks increases.

D. Testable Implications

We will now derive two sets of testable implications from our model, meant to establish the external validity of our modeling approach. The first set of predictions is related to the cross-market quoting behavior of market makers in response to changes in inventory after trading in other venues. The second set of implications is about the effects of the "ultracompetitive" quoting behavior described in Proposition 1.

1. Predictions About Cross-Market Quoting Behavior of Intermediaries

Our model predicts that market makers revise their quotes in one venue in response to an inventory shock in another venue. To the best of our knowledge, cross-venue quote revisions due to inventory shocks have never been investigated. Our model implies that not only should an individual market maker strategically revise quotes in all venues after a change in inventory, but also that competitors should strategically respond to this change. Our first prediction has two testable dimensions:[14]

Implication 1a (Cross-venue quote revision). Multivenue market makers post less (more) aggressive ask (bid) quotes in m after selling (buying) in $-m$ (and, symmetrically for bid quote updates).

Implication 1b (Strategic quoting responses of competitors). Competing market makers strategically revise their quotes in venue m in reaction to inventory-related quote changes of others after a trade in venue $-m$.

[13]Investigating the effect of the Chi-X entry on the liquidity of Dutch stocks, Degryse et al. (2015) find that fragmentation impairs local liquidity but improves global liquidity, consistent with our model.

[14]In Section 4.C in the Supplementary Material, we investigate an additional dimension and test whether intermediaries submit more inventory-related messages in venue m following a trade in venue $-m$.

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We acknowledge that other trading strategies implying a sequence of buy and sell trades, such as cross-venue arbitrage, could lead to order placement patterns that resemble those due to inventory considerations.[15] In case, say, the bid price in venue S jumps above the best ask in venue D, an arbitrageur might step in and sell one share in S, and buy one in D to reduce the existing price discrepancy. The submissions of buy and sell orders from the arbitrageur are empirically similar to inventory-driven strategies. A way to distinguish these strategies is to determine whether the transaction was triggered passively or actively. In case there is an arbitrage opportunity, we expect arbitrageurs to post time-sensitive orders in a venue just after triggering a transaction in another venue, due to the very short-lived nature of the opportunities.[16] In contrast, after a passive transaction (existing limit orders passively hit), we expect more messages related to inventory management. We thus control for the active triggering of the transaction in our empirical analysis.

2. Predictions About Competition and Market Spreads

Proposition 1 provides a novel prediction that relates price competitiveness to the signs of the shocks to be absorbed (identical or opposite) and to the divergence in intermediaries' inventories. In particular, we show that there exists a case of intense competition in which a very divergent intermediary posts very aggressive prices across venues to attract same-sign orders and lay off the inventory risk to which she is exposed. Due to the local competitive pressure of peers in each venue, she is forced to quote "ultra-aggressively" across venues to undercut and avoid being undercut. Implication 2 follows:

Implication 2. An intermediary's quoting aggressiveness depends on the direction of orders across venues (identical or opposite), on the divergence in inventories, and on the interaction between the two.

A consequence of Proposition 1 is that market spreads become tighter when competition is more intense, especially in the ultracompetitive case:

Implication 3. Variations in spreads in one venue depend on the direction of orders in both venues (identical or opposite), on the divergence in the intermediaries' inventories, and on the interaction between the two.

In our model, bid–ask spreads vary more in the satellite venue than in the dominant venue, due to the larger impact of the cross-market cost linkage and due to the greater variation in the intensity of the competition. Even if the shock has a smaller magnitude, the best ask price in the satellite venue may be higher than the one in the dominant venue (region A1 in Figure 1). In contrast, when divergence in inventories is very high (region B), competition heats up and the best ask price in the satellite venue is smaller than in the dominant venue (reflecting the smaller quantity to be executed).

[15] As explained in Section I, our empirical strategy already addresses the issue of changes in fundamentals.

[16] We call a transaction "active" when intermediaries trade through a liquidity demanding order such as a market or marketable order.

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Unlike variations in quoting aggressiveness, market spreads may vary for reasons other than inventory management, in particular asymmetric information. Our novel prediction is interesting because it allows us to depart from the competing adverse-selection and pure risk-sharing hypotheses. First, in case a (fast) informed trader with simultaneous access to all venues split his orders across venues, the adverse selection component of the multivenue market makers should increase. Market makers should reduce their liquidity supply in all venues (van Kervel (2015)), and spreads should increase if the sign of orders is the same across venues, as our cross-market cost linkage. Our model, however, predicts that adding an interaction term between a measure of same-sign orders and a measure of the divergence in inventories should have a negative impact on spreads, unlike the adverse-selection hypothesis. Second, in case market makers behave competitively, or in case they face constant marginal costs, the interaction term would not affect variations in the spread.[17]

III. Empirical Analysis

A. Data and Sample

Our analysis uses a proprietary data set from Euronext, one of the largest stock exchanges in the world.[18] Euronext was created in 2000 as a result of the merger of the Amsterdam, Brussels, and Paris exchanges, joined by Lisbon in 2002. Before the introduction of the Universal Trading Platform in 2009, each of the 4 exchanges maintained their domestic trading venue. As a result, firms could be multilisted on several Euronext exchanges; for example, Suez was traded in Paris and Brussels. Domestic trading venues consist of open electronic limit order markets, on which trading takes place continuously for more liquid stocks. Trading hours are from 9:00AM to 5:30PM.[19]

Our sample consists of all multitraded stocks within Euronext (46 firms), from Jan. 1, 2007 to Apr. 30, 2007 (79 trading days).[20] Data include all messages submitted and all transactions executed on the 4 exchanges with message IDs, venue IDs, participant IDs, and time stamps down to the second. Importantly, the participant ID is unique for a trading firm and remains identical across exchanges or stocks, enabling us to trace members' inventory changes and quoting behavior across time, stocks, and venues. Euronext files also provide a flag identifying whether the participant is acting as an agent (as a broker) or as a principal (i.e., either as a proprietary trader or an exchange-regulated market maker). During our sample period, Euronext exchanges were separate but harmonized (same trading hours,

[17]In Section 2.A in the Supplementary Material, we suppose that market makers behave competitively. We show that the ultracompetitive case is not obtained for same-sign shocks and a high divergence in inventories.

[18]We test implications of our model using a limit order book environment, but model imperfect competition in quote-driven markets. In Section 3.B in the Supplementary Material, we discuss the robustness of our empirical predictions to our modeling choices.

[19]We discard the first 5 minutes after the open and the last 5 minutes before the close to avoid any contaminating effects from opening and closing call auctions.

[20]Four trading days are dropped in January due to missing message data.

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trading fees, or trading rules) and the payment of membership fees granted access to all Euronext markets. Note also that, during this period (pre-MiFID environment), trading was concentrated on Euronext. For all these reasons, Euronext is an excellent environment to test the predictions of our model.

We drop firms that do not trade in euros or that trade via a twice-daily call auction. We further drop firms that are cross-listed outside the Euronext perimeter (e.g., Allianz, General Electric, and Telefonica). The final sample comprises 15 stocks. Table 1 presents descriptive statistics and shows that firms in our sample are representative of Europe: The average firm has a market capitalization of 33.5 billion euros and a stock price of 42 euros. Trading activity varies from 45.4 million to 0.04 million euros traded per stock day. Liquidity proxied by the difference between the Best Bid and Offer prices across all venues (denoted EBBO) varies from 4 bps (large-cap stocks) to 81 bps (medium-cap stocks). Our study focuses on proprietary trading, which in our sample constitutes, on average, 60% of all messages submitted and 39% of the volume traded.

We use the primary market as the (exogenous) criteria for determining which exchange is the dominant market. Table 2 reports statistics computed for dominant

TABLE 1

Summary Statistics for Stocks Characteristics

Table 1 reports cross-sectional averages for stocks' characteristics of our sample. The sample consists of 15 cross-listed stocks on Euronext exchanges from Jan. 2, 2007 to Apr. 30, 2007 (79 trading days) that meet the selection criteria defined in Section III. Quotes and trades data come from Euronext proprietary data. Daily measures are computed from 9:05AM to 5:25PM. MCAP is the market capitalization from Compustat Global (in millions of euros). TR_PRICE is the traded stock price (in euros). TR_VOLUME is the (daily) number of shares multiplied by the stock price, in millions of euros. EBBO_RBAS (Relative Quoted Spread) is the quoted difference between the best bid and the best ask over all Euronext exchanges, divided by the midquote, and expressed in basis points (bps). PCT_PROP_MSG is the proportion of messages sent by a trader using a proprietary account, in percentage. PCT_PROP_VOLUME is the proportion of trading volume (in euros) executed as a proprietary trader, in percentage.

Variables	Mean	Std. Dev.	p1	p99
MCAP	33,459	32,702	121	124,138
TR_PRICE	42	28	9	109
TR_VOLUME	12.92	14.60	0.04	45.40
EBBO_RBAS	17	22	4	81
PCT_PROP_MSG	60	17	26	89
PCT_PROP_VOLUME	39	9	17	49

TABLE 2

Venue-Type Statistics

Table 2 reports cross-sectional averages for quoting and trading activity measures by type of venue (Dominant vs. Satellite) for our sample. Primary markets are defined as "dominant," as opposed to "satellite" markets. RBAS is the quoted bid–ask spread divided by the midquote, in basis points (bps). TR_SIZE is the number of shares traded for each order executed. TOT_SH_VOLUME is the total number of shares traded in that venue. *Total no. of messages* is the total number of orders, order cancels, and order amends that traders place over the period in that venue. *Daily no. of best limits updates* is the total number of times there is a change in the best limits during the day. *Market share* is the proportion of trading volume executed in that venue over the total volume traded for the stock. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively, for the 2-tailed hypothesis test that the coefficient equals 0.

Variables	Dominant Venue	Satellite Venue	Diff. (*z*-Stat)
RBAS (in bps)	30	80	(2.344)**
TR_SIZE	873	470	(−1.804)*
TOT_SH_VOLUME	11,200,000	1,756,304	(−2.634)***
Total no. of messages	15,890	10,796	(−1.141)
Daily no. of best limits updates	7,839	4,926	(−1.224)
Market share (in %)	75.51	24.49	(−3.380)***

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and satellite markets. The average market share of each satellite market is 24.5%. Trade size is significantly smaller (almost by one-half) on satellite markets, which is consistent with the hypotheses of our model. Satellite venues are more illiquid and less active: Quoted bid–ask spreads are almost 4 times larger than those of dominant markets, and daily trading volume is 6 times less important. Interestingly, there are no significant differences between the two venues in terms of the daily number of messages and the daily number of updates of best quotes. These statistics suggest that satellite markets are less active, less deep, and less liquid, but closely monitored and actively updated.

B. Participants and Intermediaries

We keep 98 Euronext members trading on their own account and drop pure brokers. We then keep participants who behave as multivenue intermediaries by submitting limit orders *simultaneously* on two different venues, at least once, during our trading period. Overall, we follow 30 intermediaries, among which 6 IDs are exchange-regulated market makers (registered as such at least in one stock in sample), called hereafter DMM.[21,22]

Because their market-making obligations differ, we classify our intermediaries as DMM and non-DMM. Non-DMMs consist mainly of banks (U.S. banks such as JP Morgan and Goldman Sachs, and European banks such as Deutsche Bank and BNP Paribas) and hedge funds (Citadel). DMMs are represented by NYSE and Dutch specialists (IMC Securities, Timber Hill, and Van der Moolen Effecten Specialist). Table 3 shows that, on average, DMMs trade less, but are much more active in terms of messages (higher number of messages and message-to-trade ratio). DMMs modify more orders but cancel less than non-DMMs. Trading and quoting activity of DMMs is essentially proprietary, whereas non-DMMs exhibit a significantly smaller percentage of proprietary orders, illustrating that non-DMMs may possess a brokerage arm. During the day or at the end of the trading day, DMMs also hold less inventory, suggesting a more active inventory management.

C. Tracking the Quoting Behavior of Intermediaries

We build, in two steps, a measure tracking the positioning of the individual best quotes of an intermediary in the limit order book. We first construct the individual best bid and ask quotes, namely, those which correspond to the highest buy limit order and lowest sell limit order posted by each intermediary (when they exist) in a venue. We track 16,272,934 limit orders so as to be able to determine any changes (down to the second) in the individual best bid and ask quotes at any time in any venue. Second, from individual bid–ask spreads, we build a measure of quoting aggressiveness consisting of the (absolute) distance at time t of intermediary i's

[21]The DMM mechanism was implemented in 2001 to harmonize the Amsterdam, Brussels, and Paris exchanges, replacing all existing categories of registered market makers. DMMs are appointed and monitored by Euronext (and not by an issuer). DMMs commit to a specific spread, depth, and presence. In compensation for providing quotes, trading fees are partially or totally waived.

[22]DMMs do not have any trading privileges over other traders.

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TABLE 3

Trader-Type Statistics

Table 3 reports average trading, orders, and positions for individual designated market makers (DMMs) and non-DMMs for the 15 cross-listed stocks within the Euronext stock exchange. A DMM is an exchange-regulated liquidity provider. Averages are computed over member stock. The sample consists of 30 multivenue intermediaries, among which 6 IDs are DMMs. *No. of participants* is the average number of traders in each stock day. *No. of trades* is the daily number of transactions executed by a trader. *No. of messages* is the daily number of new orders, order cancels, and order amends that a trader submits on a proprietary account. *Message-to-trade ratio* is the number of messages sent for each trade by a trader. *Percentage of modified orders* is the ratio of the number of order amends that a trader places to the total number of messages placed by a trader. *Percentage of cancelled orders* is the ratio of the number of order cancels to the total number of messages placed by the trader. *Percentage of proprietary messages* is the proportion of messages sent by a trader using a proprietary account. *Max intra. inv.* is the trader's maximum intraday dollar volume inventory position. *Closing inv. ratio* is the absolute value of a trader's end-of-day euro volume inventory scaled by that trader's euro daily trading volume. *Two-sided in D and S (global market-making strategy)* is the percentage of times a trader simultaneously submits limit buy and sell orders in venues D and S. *Two-sided in D* is the percentage of times a trader simultaneously submits limit buy and sell orders in venue D. *Two-sided in S* is the percentage of times a trader simultaneously submits limit buy and sell orders in venue S. ΔDIST_Q is the change in quoting aggressiveness of intermediary i observed in venue S during the 20 seconds following a trade in D, as follows:

$$\Delta\text{DIST\_Q}^i_{[t,t+20]} = \overline{|Q^* - Q^i|}_{t+1,t+20} - \left|Q^* - Q^i\right|_t,$$

where Q^* is the Best Market Quote and Q^i is the intermediary i's best quote. $\left|Q^* - Q^i\right|_t$ is i's quoting aggressiveness in S prevailing at time t of the transaction in D. $\overline{|Q^* - Q^i|}_{t+1,t+20}$ is the average quoting aggressiveness of i over the 20 seconds following the trade executed at time t ($Q = A$ (Ask), B (Bid)). Quoting aggressiveness is standardized by the prevailing midquote. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively, for the 2-tailed hypothesis test that the coefficient equals 0.

Variables	DMM	Non-DMM	Diff. (t-Stat)
No. of participants	2	12	
No. of trades	81	213	(4.61)***
No. of messages	1,733	343	(−3.78)***
Message to trade ratio	146	4	(−3.43)***
Percentage of modified orders	89%	31%	(−13.63)***
Percentage of cancelled orders	9%	31%	(5.53)***
Percentage of proprietary orders	95%	69%	(−5.20)***
Max intra. inv.	160,693	422,467	(3.47)***
Closing inv. ratio	0.34	0.45	(2.07)**
Two-sided in D and S (global MM strategy)	15%	6%	(−3.00)***
Two-sided in D	29%	22%	(−0.89)
Two-sided in S	78%	19%	(−7.87)***
$\Delta\text{DIST\_B}_{[t,t+20]}$ (after buying in D; bps)	0.50	−0.02	(−17.62)***
$\Delta\text{DIST\_A}_{[t,t+20]}$ (after selling in D; bps)	0.54	−0.05	(−20.90)**

individual best quote, denoted by Q^i, from the best market quote Q^*: $\text{DIST\_Q}^i \equiv \left|Q^* - Q^i\right|_t$, where $Q = A$ (Ask), B (Bid). We focus on *changes* in quoting aggressiveness during the θ seconds following the execution of a trade at time t by intermediary i: $\Delta\text{DIST\_Q}^i_{[t,t+\theta]} = \overline{|Q^* - Q^i|}_{t+1,t+\theta} - \left|Q^* - Q^i\right|_t$, where $\overline{|Q^* - Q^i|}_{t+1,t+\theta}$ is the quoting aggressiveness averaged over the θ seconds between time $t+1$ and time $t+\theta$. In order to be able to compare the quoting aggressiveness across stocks, we standardize this measure by the midpoint of the prevailing inside spread at the time of the transaction. Note that using the distance at any time t of intermediary i's quotes from inside spreads allows controlling for changes in information caused by order flows or public information, dynamically incorporated in both the market prices and the intermediaries' quotes. Our measure captures changes in quote revision due to inventory management only.

Table 3 shows that DMMs provide liquidity on the 2 sides of the book more actively in satellite venues ("two-sided in S"), and do so more often than non-DMMs. DMMs are sometimes simultaneously on both the bid and ask sides of both the satellite and dominant venues, and significantly more often than non-DMMs ("two-sided in D and S"). This finding corroborates the ability of multivenue intermediaries to choose which shocks to absorb. Moreover, DMMs decrease their quoting aggressiveness on the bid side (resp. ask side) by 0.50 bps in the satellite venue after buying (resp. selling) in the dominant venue. Non-DMMs do not revise their quoting aggressiveness.

D. Testing the Strategic Impact of Cross-Market Inventory Costs

This section investigates the impact of the cross-market inventory cost linkage on intermediaries' quoting strategies, using two steps. The first step focuses on intermediary's revision of their quotes after buying or selling (Implication 1a). The second step studies the response of competitors to a change in the inventory of member i (Implication 1b). In our model, quoting aggressiveness and changes in bid–ask spreads vary more in the satellite venue than in the dominant venue, due to the larger impact of the cross-market cost linkage and larger variations in competition intensity. All tests thus focus on the satellite markets.

In the two sets of tests, the generating event is a transaction. To take into account order splitting, we consolidate consecutive trades reported with the same time stamp (second), executed in the same direction, at the same price, and initiated by the same intermediary into one trade (as suggested by Upson, McInish, and Johnson (2018)). The time window considered for our empirical tests consists of the first 60 seconds following a trade, split into two subperiods. Our identification strategy relies on the assumption that intermediary i will first revise their quotes to reflect the change in inventory caused by the transaction, and then her competitors will react to the observable changes in the quotes that i might have induced. This time delay in the competitors' reaction is justified by the fact that competitors will probably not react immediately at the time of the trade (their inventory has not changed). Competitors change their quoting aggressiveness only if they observe some price revision in the book that affects the degree of competition (from "low" to "intense," or vice versa). Moreover, during the period of our study, the Euronext market data were not yet consolidated into one feed, and with implicit capacity/attention constraints, inaction of intermediaries during a short period of time is likely in less active venues (see, e.g., Corwin and Coughenour (2008)). We therefore split the 60-second time window in two. We measure changes in quoting aggressiveness of intermediary i during the first 20 seconds after executing a trade, and changes in quoting aggressiveness of her competitors between the time of the transaction and the last 40 seconds of the 60-second time window.[23]

1. Analysis of Cross-Market Quoting Aggressiveness After a Trade

In what follows, we investigate quote revisions by distinguishing between a positive change in inventory and a negative one and whether cross-market quotes updates are on the same side of the trade from those which are on opposite sides. We expect a decrease in quoting aggressiveness on the side of the transaction. For instance, after selling in venue $-m$, i might no longer be able to afford selling more and decrease her quoting aggressiveness on the ask side. The larger the negative change in inventory caused by the trade, the more i should revise quotes so as

[23]Figure IA.5 in the Supplementary Material summarizes the time window considered for the empirical tests detailed below.

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to be more distant from the best ask price of the market, that is, $\Delta\text{DIST\_A}^i \equiv \Delta\left|A^* - A^i\right|_{t,t+20} > 0$ after selling. By symmetry, we expect that a similar relation holds for the bid side: $\Delta\text{DIST\_B}^i \equiv \Delta\left|B^* - B^i\right|_{t,t+20} > 0$ after intermediary i buys.

In contrast, the quoting aggressiveness following a transaction on the opposite side is expected to increase: That is, after selling (resp. buying), intermediary i is expected to be more willing to buy (resp. to sell), and should revise her bid (resp. ask) quote to be closer to the best bid (resp. best ask): $\Delta\text{DIST\_B}^i < 0$ after selling (resp. $\Delta\text{DIST\_A}^i < 0$ after buying). This cross-market quote revision on the opposite side is, however, expected to be harder to detect. This requires a very large change in inventory for i to revise her quotes so that they will form one side of the inside spread in the other venues. Moreover, the satellite market being more costly, i might choose to wait beyond the best market prices in S while being on the inside spread in D.

We test Implication 1a by running the following regression:

$$(7) \qquad \Delta\text{DIST\_Q}^i_{s,[t,t+20]} = \alpha + \beta_1 \text{DMM}^i_s + \beta_2\left|\Delta I^i_{s,t}\right| + \beta_3 \text{DMM}^i_s \times \left|\Delta I^i_{s,t}\right| + \lambda_d + \mu_s + \gamma W^i_{s,t} + \varepsilon^i_{s,t},$$

where the main explanatory variables are DMM^i_s, a dummy variable that takes the value of 1 if i is registered as a DMM at least on one venue on which stock s is traded and $|\Delta I^i_{s,t}|$, the (logarithm) absolute change in inventory of i in euros due to a trade at time t in stock s. λ_d is a day fixed effect, μ_s is a stock fixed effect, and $W_{i,s,t}$ is a vector of control variables which includes the (logarithm) transaction price (TR_PRICE) and a dummy variable that takes the value of 1 if the trade is actively triggered (TR_TYPE). We also include VOLUME_{t-300}, which is the lagged trading volume over the past 300 seconds and $|\text{RET}_{t-300}|$, the return volatility during the 300 seconds prior to the transaction, which control for market conditions in stock s at time t of the transaction (Hasbrouck and Saar (2009)). All variables are detailed in Table IA.1 in the Supplementary Material. The independent variable of interest is the interaction term between the DMM dummy and the continuous variable $|\Delta I^i_{s,t}|$.

Table 4 presents the results. Panel A presents the estimates for a positive change in inventory (after buying), whereas Panel B presents the results for a negative change. Column 1 of Panels A and B confirms the results of the univariate tests: DMMs are significantly less aggressive on the side of the transaction immediately after the transaction. Quoting aggressiveness decreases by around 0.6 bps after buying or selling. Column 2 of Panels A and B shows that the larger the change in inventory, the less aggressive DMMs are on the side of the transaction. For a change in inventory by 1 standard deviation, DMMs decrease their quoting aggressiveness on the side of the transaction by 0.16 bps, which is equal to 30% of the unconditional average change in quoting aggressiveness of i. Column 4 of Panels A and B shows that all intermediaries significantly increase their quoting aggressiveness after a transaction on the opposite side. DMMs seem not to behave differently from non-DMMs (column 3 of Panels A and B is not statistically significant). We can further show that DMMs significantly revise their quotes when they are passively hit, whereas non-DMMs do so when they

TABLE 4

Cross-Market Quotes Revisions

Table 4 documents the determinants of cross-market quote revisions after a trade in the dominant market. Panel A reports how much an intermediary revises her quotes in *S after buying* in *D*. Panel B refers to cross-market quotes revisions in *S after selling* in *D*. The dependent variable is ΔDIST_Q, a measure of changes in quoting aggressiveness calculated during the 20 seconds following a trade, described in the caption of Table 3 ($Q = A$ (Ask), B (Bid)). We distinguish between changes in relative quoting aggressiveness *on the same side* of the trade and *on the opposite side* of the trade. The main explanatory variables are DMM (an indicator variable taking the value of 1 if the trader is a designated market maker for the stock, and 0 otherwise), $|\Delta I|$ (the magnitude of the change in euro inventory due to the transaction, expressed in logarithm), and the interaction term DMM × $|\Delta I|$. The control variables are the (logarithm) price of the transaction (TR_PRICE), a dummy variable that takes the value of 1 if the trade is actively triggered (TR_TYPE), the lagged trading volume over the past 300 seconds (VOLUME_{t-300}), and the return volatility during the 300 seconds prior to the trade ($|\text{RET}|_{t-300}$). Estimates are from panel regressions with intermediary-stock and day fixed effects. The *t*-statistics are calculated using clustered (by stock-intermediary) standard errors. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively, for the 2-tailed hypothesis test that the coefficient equals 0.

Panel A. After Buying

	Same-Side $\Delta\text{DIST\_B}_{[t,t+20]}$		Opposite-Side $\Delta\text{DIST\_A}_{[t,t+20]}$	
Determinants	1	2	3	4
DMM × $\|\Delta I\|$		0.093*		0.104
		(1.80)		(1.36)
$\|\Delta I\|$		0.013		−0.068*
		(0.99)		(−1.95)
DMM	0.592***	−0.314	0.89	−0.123
	(2.65)	(−0.84)	(1.36)	(−0.22)
Intercept	2.379	2.27	−1.445	−0.707
	(1.57)	(1.48)	(−0.56)	(−0.27)
Control variables	Yes	Yes	Yes	Yes
Stock/day FE	Yes	Yes	Yes	Yes
N	60,518	60,518	58,852	58,852
Adj. R^2	0.01	0.01	0.02	0.02

Panel B. After Selling

Determinants	Same-Side $\Delta\text{DIST\_A}_{[t,t+20]}$		Opposite-Side $\Delta\text{DIST\_B}_{[t,t+20]}$	
	1	2	3	4
DMM × $\|\Delta I\|$		0.087*		0.103
		(1.73)		(1.40)
$\|\Delta I\|$		0.028		−0.056*
		(1.42)		(−1.70)
DMM	0.612***	−0.155	0.559	−0.446
	(3.24)	(−0.36)	(1.20)	(−1.01)
Intercept	0.491	0.27	−0.928*	−0.248
	(0.28)	(0.16)	(−0.28)	(−0.07)
Control variables	Yes	Yes	Yes	Yes
Stock/day FE	Yes	Yes	Yes	Yes
N	61,439	61,439	60,833	60,833
Adj. R^2	0.01	0.01	0.02	0.02

actively take liquidity.[24] Results related to the DMM category are thus consistent with Implication 1a of our model.

2. Strategic Quoting Responses of Competitors

This section addresses whether other intermediaries strategically respond to changes in inventory of intermediary *i* (Implication 1b). Again, each trade event is an observation. We exclude trades of non-DMMs because Section III.D.1 shows

[24]The results are shown in Table IA.3 in the Supplementary Material.

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that we fail to find any statistically significant quoting behavior for this category associated with our model.

We investigate competitors' strategic responses once they have observed potential changes in quotes submitted by DMM i immediately after she has traded. If competitors behave strategically, we expect a positive relation between changes in quoting aggressiveness of intermediary i and those of her competitors. If i decreases (resp. increases) her quoting aggressiveness, then competitors react by decreasing (resp. increasing) theirs. We test this relation using the following regression model:

$$(8)\quad \Delta\text{DIST\_Q}^{-i}_{s,[t+21,t+60]} = \alpha + \beta_1 \Delta\text{DIST\_Q}^{i}_{s,[t,t+20]} + \lambda_d + \mu_s + \gamma W^{i}_{s,t} + \varepsilon^{i}_{s,t},$$

where the dependent variable $\Delta\text{DIST\_Q}^{-i}_{s,[t+21,t+60]}$ measures changes in quoting aggressiveness of competitors $-i$ between t and the last 40 seconds of the 60-second time window following the trade at time t. The main independent variable ($\Delta\text{DIST\_Q}^{i}_{s,[t,t+20]}$) is the change in quoting aggressiveness of DMM i during the first 20 seconds following her trade.

Table 5 presents the estimation results. Panel A focuses on the buy side, whereas Panel B focuses on the sell side of the limit order book. Changes in quoting aggressiveness of competitors $-i$ and changes in quoting aggressiveness of DMM i are significantly and positively related on the same side of the trade. A decrease in the quoting aggressiveness of DMM i by 1 standard deviation decreases the quoting aggressiveness of competitors by 0.22 bps on the bid side and by 0.34 bps on the ask side after a trade on the same side, which is consistent with Implication 2. We do not observe significant changes in quoting aggressiveness of competitors on the opposite side. This is not surprising, as we did not find any significant changes in quoting aggressiveness of DMMs after a trade on the opposite side in the previous section.

E. "Ultracompetitive" Effects

So far, we have established that DMMs and their competitors behave in a way consistent with our strategic cross-venue market-making model. We now test one of the main predictions of our imperfect competition model, the "ultracompetition" case. First, we test whether DMMs behave more aggressively when they hold divergent inventory and have the ability to execute inventory-reducing trades on more than one venue. Second, we test the relation between market spreads and ultracompetitive conditions. To this end, all variables are calculated at 20-minute intervals.

1. Ultracompetitive Effects and Quoting Aggressiveness

This section explores whether intermediaries' quoting aggressiveness is related to the intensity of price competition between intermediaries, proxied by the divergence in their inventories. We recall that the outcome depends on whether orders have the same direction across venues (Implication 2). Precisely, we test:

TABLE 5

Strategic Quoting Responses of Competitors

Table 5 presents the determinants of the quoting response of competitors $-i$ in venue S after a trade by designated market maker (DMM) i at time t in venue D. The main dependent variable is the quoting response of the other $(n-1)$ competitors in venue S averaged over all peers. This variable is calculated as the difference between the average change in quoting aggressiveness of competitors between the second $t+21$ to $t+60$ compared to quote aggressiveness at time t of the transaction:

$$(11)\qquad \Delta\text{DIST\_Q}^{-i}_{t,[t+21,t+60]} = \sum_{k=1,k\neq i}^{k=n} \frac{\overline{|Q^* - Q^k|}_{t+21,t+60} - \left|Q^* - Q^k\right|_t}{n-1},$$

where $\left|Q^* - Q^k\right|_t$ is the quoting aggressiveness of competitor k at time t, defined as the distance of the quote posted by k from the market quote, and $\overline{|Q^* - Q^k|}_{t+21,t+60}$ is the average change in k's quoting aggressiveness between $t+21$ and $t+60$. We standardize this variable by the prevailing midquote. The main explanatory variable $\Delta\text{DIST\_Q}^i_{[t,t+20]}$ is the change in the quoting aggressiveness of DMM i in venue S during the first 20 seconds after she trades in the dominant market ($Q=A$ (Ask) or B (Bid)). This variable is detailed in the caption of Table 4. Panel A reports how much competitors of DMM i revise their bid position in venue S after her transaction in venue D. Panel B reports how much competitors of DMM i revise their ask position in venue S after i trades in venue D. Each panel has 2 columns depending on the side of the trade in the book (same or opposite of quotes). Control variables (TR_PRICE, TR_TYPE, VOLUME_{t-300}, and $|\text{RET}|_{t-300}$) are defined in the caption of Table 4. Estimates are from panel regressions with stock and day fixed effects. The t-statistics are calculated using clustered (by stock-intermediary) standard errors. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively, for the 2-tailed hypothesis test that the coefficient equals 0.

Panel A. Bid-Side Revision

Determinants	$\Delta\text{DIST\_B}^{-i}_{t,[t+21,t+60]}$ Same Side	Opposite Side
	1	2
$\Delta\text{DIST\_B}^i_{t,[t,t+20]}$	0.051**	0.037
	(2.15)	(1.36)
Intercept	−0.112	9.083**
	(−0.02)	(2.27)
Control variables	Yes	Yes
Stock/day FE	Yes	Yes
N	14,974	15,193
Adj. R^2	0.02	0.01

Panel B. Ask-Side Revision

Determinants	$\Delta\text{DIST\_A}^{-i}_{[t+21,t+60]}$ Same Side	Opposite Side
	1	2
$\Delta\text{DIST\_A}^i_{[t,t+20]}$	0.083***	0.005
	(3.13)	(0.17)
Intercept	−2.97	3.942
	(−0.86)	(1.05)
Control variables	Yes	Yes
Stock/day FE	Yes	Yes
N	14,956	15,158
Adj. R^2	0.02	0.01

$$(9)\qquad \overline{\text{DIST\_Q}}^i_{s,\tau} = \alpha + \beta_1 \text{SAME}_{s,\tau} + \beta_2 \overline{RI}^i_{s,\tau-1} + \beta_3 \text{SAME}_{s,\tau} \times \overline{RI}^i_{s,\tau-1} + \lambda_d + \mu^i + \gamma W^i_{s,\tau} + \varepsilon^i_{s,\tau},$$

where the dependent variable is a measure of individual quoting aggressiveness. Because equation (9) is not trade by trade, we build another measure of quoting aggressiveness adapted to the 20-minute aggregation setting. We first consider the individual quoting aggressiveness for both bid and ask prices. We then keep the most aggressive side and build time-weighted quoting aggressiveness for each trader over each 20-minute interval, that is, $\overline{\text{DIST\_Q}}^i_{s,\tau} = \overline{\min\left(|A^* - A^i|, |B^* - B^i|\right)}_{s,\tau}$. The explanatory variables are SAME, a dummy variable that takes the value of

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1 if the order flows in both venues have the same direction, $\overline{\mathrm{RI}}^i$, which is a measure of the divergence of intermediary i's inventory relative to the median inventory across all its peers (excluding i), and the interaction between SAME and $\overline{\mathrm{RI}}^i$, which is the variable of interest. Note that $\overline{\mathrm{DIST\_Q}}^i$ and $\overline{\mathrm{RI}}^i$ are calculated using a panel "second × stock × intermediary" and then averaged over each 20-minute interval.

From Proposition 1 and Figure 1, we expect $\beta_3 < 0$, since intermediary i posts ultracompetitive prices when she is very divergent and order flows sent to the two venues have the same direction (region B in Figure 1). The coefficient β_1 can be positive or negative (regions A1, A2, and B in Figure 1). Using inventory management predictions, we expect $\beta_2 < 0$: The more divergent i is, the more aggressive she is expected to behave.

Table 6 presents three specifications according to the controls used (day fixed effects and control for the level of trading activity). For all specifications, the interaction term is negative and statistically significant (t-stats vary from −2.12 to −2.23), suggesting that inventory divergence is associated with a greater quoting aggressiveness of DMMs, especially when order flows sent to the two venues have the same direction. An increase by 1 standard deviation in the inventory divergence increases the quoting aggressiveness by between 1.2 bps (for specification 1) to 0.4 bps (for specification 3), which is 13% or 5% of the unconditional average in quoting aggressiveness of DMMs. These results are consistent with the intense price competition illustrated in regions A2 and B in Figure 1.

TABLE 6

Determinants of Cross-Market Quoting Aggressiveness

Table 6 presents estimates of the relation between the quoting aggressiveness of intermediary i, the divergence in i's inventory, and the direction of order flows across venues. The left-hand side variable is a measure of the quoting aggressiveness of intermediary i on market S, normalized by the price and time-weighted over each 20-minute interval. The explanatory variables are the (lagged) inventory divergence $\left(\left|\overline{\mathrm{RI}^i}\right|_{\tau-1}\right)$, which is the time-weighted average distance between intermediary i's inventory and the median inventory over all peers excluding i; SAME is a dummy variable that takes the value of 1 if order flows across venues have the same direction: TR_IMB_S × TR_IMB_D > 0, and 0 if order flows have opposite directions. TR_IMB_M is defined as the number of buyer-initiated trades minus the number of seller-initiated trades during the last 20-minute interval in venue m. The variable of interest is the interaction term SAME × $\left|\overline{\mathrm{RI}^i}\right|_{\tau-1}$. The control variables are i) the magnitude of the lagged inventory of i $\left(\left|\overline{I^i}\right|_{\tau-1}\right)$ and ii) the number of trades in S over the 20-minute interval (NB_TRADE_S). Estimates are from panel regressions with intermediary and day fixed effects. The t-statistics are calculated using standard errors clustered by firm. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively, for the 2-tailed hypothesis test that the coefficient equals 0.

	$\overline{\mathrm{DIST\_Q}}^i$		
Determinants	1	2	3
SAME × $\left\|\overline{\mathrm{RI}^i}\right\|_{\tau-1}$	−0.055**	−0.053**	−0.052**
	(−2.23)	(−2.19)	(−2.12)
$\left\|\overline{\mathrm{RI}^i}\right\|_{\tau-1}$	−0.132***	−0.124***	−0.009
	(−6.85)	(−6.60)	(−0.39)
SAME	1.181***	1.109***	1.149***
	(3.53)	(3.33)	(3.51)
Intercept	10.5***	9.868***	3.518
	(45.67)	(39.61)	(1.46)
Control variables	No	Yes	Yes
Day FE	No	No	Yes
Intermediary FE	Yes	Yes	Yes
N	7,827	7,827	7,827
Adj. R^2	0.49	0.5	0.53

TABLE 7

Determinants of Variations in Bid–Ask Spreads in the Satellite Market

Table 7 presents the estimates of the relation between changes in relative bid–ask spreads in the satellite market and the divergence in intermediaries' inventories and the direction of order flows across venues. The left-hand side variable is a measure of the change in the relative bid–ask spread (ΔRBAS) on *S*. Column 1 uses the average RBAS over each 20-minute interval. Column 2 uses the last bid–ask spread of each 20-minute interval. The explanatory variables are the (lagged) average inventory divergence, taken over all intermediaries ($|\overline{\text{RI}}|_{\tau-1}$); SAME is a dummy variable that takes the value of 1 if order flows across venues have the same direction defined in the caption of Table 6, and the variable of interest is the interaction term, SAME $\times$ $|\overline{\text{RI}}|_{\tau-1}$, which is the product of the dummy of same-sign shocks (SAME) and $|\overline{\text{RI}}|_{\tau-1}$. The control variable is the number of trades in *S* over each 20-minute interval (NB_TRADE_S). Estimates are from panel regressions with stock and day fixed effects. *T*-statistics are calculated using standard errors clustered by firm. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively, for the 2-tailed hypothesis test that the coefficient equals 0.

	$\Delta\overline{\text{RBAS}}$	$\Delta\text{RBAS}_{\text{LAST}_\tau}$
Determinants	1	2
SAME $\times$ $\lvert\overline{\text{RI}}\rvert_{\tau-1}$	−0.114* (−1.75)	−0.11** (−2.07)
$\lvert\overline{\text{RI}}\rvert_{\tau-1}$	0.074 (1.24)	0.047 (0.75)
SAME	0.099* (1.82)	0.093** (2.01)
Intercept	−0.071 (−1.05)	−0.094 (−1.01)
Control variables	Yes	Yes
Stock/day FE	Yes	Yes
N	10,552	9,353
Adj. R^2	0.02	0.04

2. Ultracompetitive Effects and Market Spreads

We now investigate whether market spreads are influenced by variations in price competition (Implication 3). Using a specification somewhat similar to equation (9), we run the following panel regression at the stock level:

$$\text{(10)}\quad \Delta\text{RBAS}_{s,\tau} = \alpha + \beta_1 \text{SAME}_{s,\tau} + \beta_2 \overline{\text{RI}}_{s,\tau-1} + \beta_3 \text{SAME}_{s,\tau} \times \overline{\text{RI}}_{s,\tau-1} + \lambda_d + \mu_s + \gamma W_{s,\tau} + \varepsilon_{s,\tau},$$

where the dependent variable is a measure of the change in the relative bid–ask spread, denoted by ΔRBAS. The main explanatory variables are SAME, a dummy variable that takes the value of 1 if order flows have the same direction in the two venues, and $\overline{\text{RI}}$, which is the average over all intermediaries of their inventory divergence.

Using Lemma 1 and Proposition 1, we expect $\beta_1 > 0$ due to the cumulative cross-market cost linkage effect observed when shocks have the same sign. The inventory divergence with coefficient β_2 controls for any confounding effect resulting from basic inventory models. In centralized markets, its sign would be unambiguously negative, which is a basic prediction of the inventory framework. In fragmented markets, its sign depends on whether shocks hitting venues have the same sign, or not (due to the cross-market cost linkage effect). From our model, we expect $\beta_3 < 0$: In case of both a large inventory divergence and same-sign shocks, at least one intermediary competes intensely to execute all orders across venues. Note that this interaction term allows us to distinguish our predictions from those of an adverse selection model, since the latter would predict $\beta_3 \geq 0$. Finally, we control for the activity in the venue, affecting bid–ask spreads. All specifications include day and stock fixed effects and use clustered standard errors by stock.

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Table 7 presents two specifications: the first using changes in bid–ask spreads averaged over each 20-minute interval (column 1) and the second with changes in the last bid–ask spread over each 20-minute interval (column 2). The main conclusions from the analysis are as follows: First, bid–ask spreads significantly increase when order flows have the same direction across venues. The coefficients are positive, ranging from 0.093 to 0.099, and statistically significant at least at the 10% level. This result is consistent with the cross-market cost linkage. Second, the interaction term between same-sign order flows and divergence in inventories has a negative and statistically significant effect on changes in the bid–ask spread. This result is robust across the two specifications, with similar magnitudes and significance levels. The estimates in column 1 (resp. column 2) imply that a 1-standard-deviation shock in the inventory divergence ($\overline{\text{RI}}$) is associated with a negative change of 1.2 bps (resp. 1.5 bps in column 2) in relative bid–ask spreads. Spreads in the satellite markets are thus significantly lower when there are intermediaries holding divergent inventory and when order flows have the same direction across venues, supporting Implication 3.

IV. Conclusion

We have developed a two-venue duopoly model and shown that the cross-market cost linkage and the possibility to undercut in only one venue can increase competition and enhance liquidity. We have tested our predictions using nonanonymized message and trade data from identical but separate order books for the same security within Euronext. We have uncovered new evidence of strategic quoting effects related to cross-venue market-making strategies and have found that local bid–ask spreads vary in a way that is only predicted by our model.

Although our model highlights how fragmentation may alter market-making, it might, however, not be suited to analyze the welfare consequences of a change in regulation that would, for instance, affect the number of venues and of market makers. More research is needed to model imperfect competition in limit order books allowing for the endogenous entry of strategic liquidity providers and demanders.

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109022000394.

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