Adverse selection, transaction fees, and multi-market trading[♣]

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Abstract

We study the interaction of adverse selection and transaction fees in a fragmented financial market. Absent a trade-through prohibition, liquidity providers on alternative trading platforms may be exposed to an increased adverse selection risk due to frictions in traders' market access. As a consequence, the main market dominates (offers better quotes) frequently albeit charging higher transaction fees. The empirical analysis of a recent dataset of trading in French and German stocks suggests that trades on Chi-X, a recently launched low-cost trading platform, carry significantly more private information than those executed in the Primary Markets. Consistent with our theory, we find a negative relationship between the competitiveness of Chi-X's quotes and this *excess* adverse selection risk faced by liquidity providers in the cross-section. Our results suggest that trade-throughs are a serious obstacle to inter-market competition.

Keywords: MiFID, Inter-market competition, Adverse selection, Transaction fees

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1. Introduction

The introduction of the Markets in Financial Instruments Directive (MiFID) in late 2007 has spawned competition among stock exchanges across Europe. Under the new legislation, alternative trading platforms (so-called Multilateral Trading Facilities, henceforth MTFs) may directly compete with the national stock exchanges (Primary Markets) for customer order flow. Ultimately, MiFID aims at creating a level playing field that promotes competition between market centers and fosters innovation.

One issue that has received a great deal of attention in the context of inter-market competition is the design of best execution policies. Under MiFID, intermediaries such as banks and brokers bear the entire responsibility for obtaining "the best possible result" for their clients' orders. Importantly, best execution is not only based on prices but rather permits the consideration of a wide array of additional execution characteristics such as liquidity, order size, and the likelihood of execution, among others (see e.g. Petrella [2009] and Gomber and Gsell [2010] for details). Consequently, MiFID does not formally enforce inter-market price priority and orders are permitted execute at a price that is inferior to the best *available* price across venues ("trade-throughs"). This differs considerably from the rules that are in place in the United States under Reg NMS, which mandates exchanges to re-route orders to other market centers if those are offering a better price ("trade-through rule").

In this article, we argue that allowing for trade-throughs may benefit the Primary Markets and therefore limit inter-market competition. To this end, we study how adverse selection and transaction fees interact in a fragmented financial market where trade-throughs are not prohibited. Inspired by the current market setting in Europe, we develop an extension of the Glosten and Milgrom [1985] sequential trade model where liquidity providers post quotes in two separate trading platforms, the Primary Market and a low-cost MTF. A key ingredient in our model is the existence of market access frictions. Following Foucault and Menkveld [2008], we assume that the Primary Market is accessible by all agents in the economy, while trading on the MTF requires a so-called smart order routing system that is only available to a subset of the trader population. Due to the absence of a trade-through rule, this access friction gives rise to inter-market differences in the adverse selection risk faced by liquidity providers. If informed traders are more likely than uninformed traders to be "smart routers", situations can arise where the Primary Market offers better quotes frequently despite charging higher transaction fees.

The analysis of a recent sample of transactions and quote data for German and French stocks confirms the existence of imperfections in traders' routing abilities, as only about every second trade originates from agents with perfect acess to Chi-X, a recently launched MTF. Moreover, we find that trades executed on this new trading platform carry significantly more private information than their counterparts on the Primary Markets, while trade-throughs are particularly uninformative. This implies that liquidity providers on the MTF incur a higher adverse selection risk precisely because an important fraction of the uninformed order flow is held captive in the Primary Markets. Cross-sectional regressions provide empirical support for our theory, as we find that this excess adverse selection risk is negatively related to Chi-X's presence at the inside quote.

These results have important implications for the design of best executions policies. Allowing for trade-throughs benefits the Primary Markets because captive traders constitute a stable customer basis that is not subject to competition from other exchanges. Additionally, liquidity providers on alternative trading venues are exposed to a higher adverse selection risk because smart routers are more likely to be informed than the average trader. This excess risk frequently results in poor quotes and therefore diverts additional order flow from smart routers to the Primary Markets. Therefore, trade-throughs constitute an important obstacle for inter-market competition as the cheaper market (in terms of transaction fees) may end up with very little order flow, even from agents that have access to it. In this sense, our model supports the idea that the enforcement of inter-market price priority may foster competition between exchanges.

Our findings are in line with existing concerns about MiFID's best execution policy. In the absence of inter-market linkages, market fragmentation increases the costs for monitoring markets in real-time, as it requires intermediaries to adopt a smart order routing system. For smaller market participants, the substantial costs associated with such an infrastructure may well exceed the expected benefits. Consistent with this view, a recent article in the Financial Times [2010] reports that much retail order flow is routinely routed towards the Primary Markets as small brokers shy away from investments in technology. Additionally, Ende and Lutat [2010] document a sizeable fraction of trade-throughs in European stocks, which confirms the existence of market access imperfections post-MiFID.

Moreover, recent anecdotal evidence appears consistent with our view that a higher adverse selection risk negatively affects the competitiveness of MTFs. On September 8th, 2008, the market opening on the London Stock Exchange was delayed until 4 pm in the afternoon due to a technical problem. While Chi-X and Turquoise were still available for trading in UK stocks, the market activity ceased almost completely during the LSE's system outage. A similar event occurred on Euronext on April 20th, 2009, when trading commenced with a delay of one hour. Again, trading did not migrate to the MTFs. Presumably, excessive adverse selection risk lead to a market breakdown. Yet another outage on the LSE during the afternoon of November 9th, 2009 saw some trading migrate to alternative venues. The fact that the outage occurred late in the trading day may have helped the MTFs, as much of the day's price discovery had already occurred prior to the LSE's breakdown.

This paper contributes to the existing literature on inter-market competition. While early theoretical papers (e.g. Pagano [1989] and Chowdry and Nanda [1991]) argue that markets display a natural tendency to consolidate as a consequence of liquidity externalities, there is a large empirical literature that empirically documents the existence of fragmented financial markets (e.g. Bessembinder [2003], Boehmer and Boehmer [2004], Goldstein et al. [2007], Biais et al. [2010]).

Most closely related to our paper, Foucault and Menkveld [2008] develop and test a theory of competition between two markets in an environment that allows for trade-throughs. In their model, which abstracts from uncertainty about the asset's fundamental value, risk-neutral competitive agents trade off the expected revenue from liquidity provision against order submission fees. They find that the share of liquidity provided on the alternative trading platform (weakly) increases in the proportion of smart routers. While our work shares their assumption of heterogeneity in traders' routing abilities, we consider a model with a risky asset and asymmetric information. We therefore contribute to the literature by studying the interplay of adverse selection risk and transaction fees in the context of inter-market competition under the absence of price priority across trading venues.

Naturally, our work is also closely related to a number of papers that study differences in informed trading across markets. One strand of this literature analyzes the effects of "cream-skimming" and payment for order flow (e.g. Easley et al. [1996a], Bessembinder and Kaufman [1997], Battalio et al. [1997], Parlour and Rajan [2003]). In our context, the competitiveness of alternative trading platforms is hampered by the concentration of uninformed order flow on the Primary Markets due to trade-throughs generated by captive traders. This contrasts strongly with the standard paradigm within this literature, where uninformed order flow is directed *away* from the main market center due to so-called preferencing agreements[1]. Other papers (e.g. Grammig et al. [2001], Barclay et al. [2003], Goldstein et al. [2007]) document differences in informed trading between dealer markets and anonymous electronic trading systems. Generally, these studies find order flow in electronic markets to be more informative, presumably because informed traders value the higher speed of execution offered by these venues and try to prevent information leakage due to interacting with intermediaries such as market makers. In contrast, we show that differences in informed trading across exchanges may also arise through the absence of inter-market price priority paired with frictions in traders' market access.

Finally, our model also accommodates the results of Hengelbrock and Theissen [2009], who study the market entry of the Turquoise MTF in late 2008 and find that the trading activity in larger and less volatile stocks tends to fragment more.

This paper is organized as follows. Section 2 introduces our theoretical model, while Section 3 describes the institutional environment and presents the data. Section 4 presents estimates for differences in informed trading between the Primary Markets and Chi-X, and Section 5 presents evidence on the model's empirical implication. Section 6 concludes, while proofs and tables are relegated to the appendix.

2. The Model

There is a single risky asset with liquidation value $V \in \{\overline{V}, \underline{V}\}$, where we set $\Pr(V = \overline{V}) \equiv \delta_0 = 1/2$ for simplicity. The asset can be traded on two separate trading platforms, which we denote by C(hi-X) and P(rimary Market). These markets are populated by $N^P \geq 2$ and $N^C \geq 2$ identical, risk neutral market makers, respectively, who post bid and ask quotes for a single unit of the risky asset. Market P charges a

[1] Preferencing agreements usually establish a relation between a broker and a trading platform, where brokers receive a payment for directing the entire order flow to a particular venue. This practice was pioneered by Bernhard Madoff in the 1980's.

cost c > 0 per trade to market makers, while the cost charged by market C is normalized to zero. We assume that c is very small in comparison to the asset's fundamental uncertainty, i.e. $c << (\overline{V} - \underline{V})/2$.

There is a continuum of traders, who arrive sequentially at time points t=1, …, T. Unlike Dennert [1993], we assume that each trader may buy or sell at most one unit of the asset. Moreover, agents may only trade once, directly upon entering the market. A proportion μ of the trader population is perfectly informed about the liquidation value V, while the remaining traders are uninformed. Whereas all agents can trade in market P, trading in market C requires a smart order routing system that is not available to all agents in the economy. Denote the proportion of informed and uninformed traders with smart order routing technology by θ^I and θ^U, respectively. We call those traders smart routers, while agents that can only trade in market P are named captive traders. Figure 1 in the appendix graphically depicts the structure of the trader population for the case $\theta^I > \theta^U$.

The overall proportion of smart routers is given by $\theta = \mu\theta^I + (1-\mu)\theta^U$. Let μ^{SR} and μ^{CT} denote the proportion of informed traders among smart routers and captive traders, respectively, which are given by

$$\mu^{SR} \equiv \frac{\theta^I \mu}{\theta} \qquad \mu^{CT} \equiv \frac{(1-\theta^I)\mu}{1-\theta}$$

It is easy to see that $\theta^I > \theta^U$ ($\theta^I < \theta^U$) implies $\mu^{SR} > \mu > \mu^{CT}$ ($\mu^{SR} < \mu < \mu^{CT}$).

[Insert Figure 1 about here]

Uninformed traders buy or sell with equal probability. Informed traders buy if $V = \overline{V}$ and the best ask at which they can trade is less or equal to $\overline{V}$ at the time of their arrival, and sell if $V = \underline{V}$ and the best available bid is higher or equal to $\underline{V}$. Otherwise, they do not trade. Traders always choose to trade in the market that offers the better price given their trading interest and market access.

One issue arises in situations where both venues display identical quotes, such that smart routers are indifferent between markets. Given that market makers are not required to place their quotes on a discrete grid (i.e. the tick size is zero), such ties may arise even if both trading platforms charge different fees for market orders, because ultimately all fees are borne by the market order traders (liquidity providers simply pass them on). Clearly, a positive tick size can break traders' indifference, as ties will only occur before transaction costs. Then, smart routers will rationally trade in the market that demands lower fees for market orders. As the introduction of a tick size comes at the expense of additional notation without providing further insights, we opt for a reduced-form approach and assume that smart routers always trade in market C in the case of an inter-market tie.

Assumption (Tie-breaking rule):

In the case of an inter-market tie, smart routers always trade in market C.

On the other hand, if several market makers post the same price in the same market, we assume that one of them is randomly selected (with equal probability) as a trading partner for the incoming trader. After each trading round t, market makers update their beliefs about the probability of the high outcome of the asset's liquidation value using Bayes' rule and revise their quotes accordingly. We assume that they observe each other's trades[2], which implies that they hold identical beliefs about the liquidation value at all times. Let δ_{t-1} denote this common belief prior to the arrival of the t-th trader.

For simplicity, we restrict our analysis to the bid side. Results for the ask side can be derived following exactly the same logic. Let $b_t^{i,P}$ and $b_t^{j,C}$ the quotes of market makers i and j in markets P and C, respectively, where i=1, …, N^P and j=1, …, N^C. Moreover, define the best bid in market k as $b_t^k = \max\{b_t^{1,k},...,b_t^{N^k,k}\}$ for $k \in \{P,C\}$.

Given that captive traders can only trade in the Primary Market, the probability of a sell occurring in market P is always strictly positive. On the other hand, trade may only occur in market C if the bid quote at least matches the bid prevailing in market P. This leads us to the following definition of market co-existence.

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[2] This can be interpreted as markets being subject to post-trade transparency. See Madhavan [1995] for a model without post-trade transparency.

Definition (Market co-existence):

Markets co-exist iff $b_t^C \geq b_t^P$.

We are now ready to state our main result, which provides a condition for market co-existence to obtain in equilibrium. We restrict our attention to symmetric equilibria in pure strategies.

Proposition 1:

Let $N^P \to \infty$. Then, in equilibrium, markets co-exist if and only if

$$c \geq (\overline{V} - \underline{V})(\mu^{SR} - \mu)\Psi_B(\delta_{t-1}) \qquad (1)$$

where

$$\Psi_B(\delta_{t-1}) = \frac{2\delta_{t-1}(1-\delta_{t-1})}{\left[1+\mu^{SR}(1-2\delta_{t-1})\right]\left[1+\mu(1-2\delta_{t-1})\right]}$$

Proof:

See Appendix A.

To understand the intuition behind this result, first consider the case where $\theta^I \leq \theta^U$. This implies that $\mu^{SR} \leq \mu$, i.e. the proportion of informed traders among smart routers is no greater than the proportion of informed traders in the overall trader population, such that market makers on platform C face a (weakly) lower adverse risk. Additionally, market C does not charge any transaction fees, so that the best bid on Chi-X is always strictly higher than the best bid in the Primary Market. In this case, condition (1) is necessarily satisfied as the right-hand side is always negative, such that markets co-exist.

Now consider the converse situation, where $\theta^I > \theta^U$, or equivalently $\mu^{SR} > \mu$. In this case, liquidity providers in market C face an excess adverse selection risk due to a higher proportion of informed traders among smart routers, which is captured by the right-hand side in (1). On the other hand, they do not incur the transaction fee c that is payable for transactions in market P. Clearly, the best bid on Chi-X can only match or improve upon the Primary Market if the fee savings compensate for the excess adverse selection risk. The function $\Psi_B(\delta_{t-1})$ captures the behaviour of the adverse selection differential over time: As the order flow is informative about the asset's liquidation value, market makers' beliefs δ_{t-1} converge to either zero or one as the number of trading rounds becomes large, such that $\Psi_B(\delta_{t-1})$ approaches zero. As the adverse selection risk diminishes, differences in quotes across markets are entirely determined by the difference in transaction fees, and the market co-existence condition is necessarily satisfied.

Proposition 1 has an empirical implication for Chi-X's quote competitiveness in the cross-section. In order to see this, define $\Delta AS = \max_{\delta_{t-1}} \Delta AS(\delta_{t-1})$, where $\Delta AS(\delta_{t-1}) = (\overline{V} - \underline{V})(\mu^{SR} - \mu)\Psi_B(\delta_{t-1})$. Now consider two assets, A and B, and suppose that $\Delta AS_A(\delta_{t-1}) > \Delta AS_B(\delta_{t-1})$ for all market maker beliefs δ_{t-1}, i.e. the cross-market adverse selection differential (Chi-X minus Primary Market) is always strictly greater for asset A. If $c \geq \Delta AS_A$, the market co-existence condition (1) is satisfied for all possible beliefs and the best bid on Chi-X will match or improve upon the best bid in the Primary Market throughout the entire trading day for both assets. On the other hand, condition (1) is not always satisfied if $c < \Delta AS_A$. Moreover, as $\Delta AS_A(\delta_{t-1}) > \Delta AS_B(\delta_{t-1})$ for all δ_{t-1}, there exist beliefs for which Chi-X matches or improves on the Primary Market for asset B, while the Primary Market displays a strictly better quote for asset A. The converse never holds. This leads us to the following empirical prediction.

Corollary 1:

In the cross-section, Chi-X's presence at the inside quote (weakly) decreases in the adverse selection risk differential (Chi-X minus Primary Market).

3. Institutional details and data

In the remainder of the paper, we empirically analyze a sample of transaction data from Chi-X and two Primary Markets, Euronext (Paris) and Xetra (Frankfurt), in order to validate the empirical prediction of our model (Corollary 1). Before we turn to the description and a preliminary analysis of our dataset, we provide a brief overview of the institutional details that pertain to our sample period (May – April 2008).

3.1 Institutional details

Chi-X was launched on March 30th, 2007, when it started to offer trading in German and Dutch blue chips. Later the same year, trading was extended to the largest British (June 29th), French (September 28th), and Swiss (November 23rd) equities. Several other European markets were added subsequently, and starting in late 2008, the spectrum of available stocks was extended to mid-caps. As of November 2010, almost 1,400 stocks from 15 European countries could be traded on Chi-X. According to Fidessa[3], Chi-X's market share during the first six months of 2010 exceeded 20% for Belgian, Dutch, French, German, and British blue chips.

Like virtually all European stock markets, Chi-X is organized as a continuous, fully electronic limit order market (LOM). During trading hours, participants can continuously submit, revise and cancel limit and market orders. Non-executed limit orders are stored in the limit order book, and incoming market orders execute against those. Trading is fully anonymous, both pre- and post-trade.

Chi-X offers a very simple fee structure, which is asymmetric (a so-called make/take fee scheme): Passive executions (limit orders) receive a rebate of 0.2 bps, while aggressive executions (market orders) are charged 0.3 bps. Therefore, the platforms overall revenue per trade amounts to 0.1 bps. In the US market, these make/take fee schemes have proven key to success for the ECNs.

As opposed to Chi-X, the Primary Markets under consideration in this paper (Euronext Paris and Deutsche Boerse's Xetra) do not distinguish between active and passive executions, i.e. their fee structures are symmetric. Euronext charges €1.20 plus 0.055 bps per executed order, which amounts to 0.455 bps for an average trade size of ~€30,000 (see Table 2 in Section 3.2). Xetra charges 0.552 bps per trade (subject to a minimum charge of €0.69 with a cap at €20.70), which is somewhat more expensive for the average trade size but cheaper for smaller trades. Both exchanges offer different rebate schemes for particularly active members subject to minimum activity charges. Overall, the transaction fees in both Primary Markets are

[3] See http://fragmentation.fidessa.com

relatively similar and significantly exceed those on Chi-X, particularly for orders providing liquidity[4].

Besides charging considerably lower fees, Chi-X distinguishes itself from the Primary Markets in several other aspects. Most prominently, the MTF specifically targets high frequency traders via an ultra-low system latency, which according to the platform[5] is "up to ten times faster than the fastest European primary exchange". Moreover, Chi-X offers a wider range of admissible order types such as hidden and pegged orders. While the first order type is completely invisible until executed[6], the latter type is a limit order where the limit price is "pegged" to a reference price, e.g. the best bid in the Primary Market, and is updated continuously. Finally, at the time of our sample (April-May 2008), Chi-X facilitated the undercutting of Primary Markets' quotes by offering a lower tick size for most securities. The entry of additional MTFs triggered a race for lower tick sizes in early 2009, which was ended with an agreement brokered by the Federation of European Securities Exchanges (FESE), after which the MTFs adopted the tick sizes used by the respective Primary Market.

While Chi-X only offers trading in a continuous LOM, both Xetra and Euronext additionally hold call auctions to set the opening and closing prices. Xetra also has an intraday call auction at 13:00 CET, which nevertheless generates only negligible trading volume except on days where derivative contracts expire (see Hoffmann and Van Bommel (2010)). Moreover, unlike Chi-X, the Primary Markets have a fixed set of rules that triggers an automatic call auction in times of extreme price movements (so-called volatility interruptions).

3.2 Data and preliminary analysis

Chi-X Ltd. generously provided us with a very detailed dataset for the months of April and May 2008, comprising a total of 43 trading days. The data contains information on the entire order traffic generated during this period, listing limit order additions, cancellations/modifications as well as trades separately. Timestamps are

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4 Both Xetra and Euronext have designated market makers that are committed to maintain a minimum spread and a certain depth for individual stocks. Those market participants are usually exempt from transaction fees.

5 "Chi-X celebrates its first anniversary", Chi-X press release, 07.04.2008

6 Hidden orders usually must meet minimum size requirements under MiFID.

rounded to the nearest millisecond. From this data, we reconstruct the entire limit order book as well as the best bid and offer (BBO) at each point in time. Data for trades and quotes of French and German stocks on their respective Primary Markets (Euronext and Xetra) during the corresponding time period was obtained from Reuters. Again, timestamps are rounded to the nearest millisecond. While the Chi-X data always contains a qualifier that tells us whether a market order was a buy or a sell, we sign trades on the Primary Markets using the Lee and Ready [1991] algorithm. As opposed to trades in a dealer market such as the NYSE, the risk of order misclassification is very small in a pure limit order book. Merging the BBO data from Chi-X and the Primary Markets, we obtain the European Best Bid and Offer (EBBO). We restrict our analysis to the continuous trading phase, which spans the time between 9:00 and 17:30 CET.

At the time of our sample, Chi-X was the only existing MTF and only offered trading in blue chips, such that our analysis is limited to the constituents of the CAC40 and DAX30 indices. We drop three French stocks (Arcelor, EADS and Dexia) from our sample as they are simultaneously traded on other European markets (Amsterdam, Frankfurt, and Brussels, respectively), such that our final sample comprises of 67 stocks.

[Insert Tables 1 and 2 about here]

Table 1 in the appendix lists the stocks contained in our sample, while Table 2 contains summary statistics on the trading activity during our sample period. Overall, trading on Chi-X accounts on average for 5.95% of total trading volume, or 12.31% in terms of trades. Consequently, the average trade size on the Primary Markets (€28,990) is more than twice as large as the average transaction value on Chi-X (€12,620). This is in line with Chi-X being largely dominated by algorithmic traders, who have been shown to employ much smaller trade sizes than human traders (see e.g. Hendershott and Riordan [2009]). Moreover, it is consistent with small orders being particularly cheap to execute on the MTF due to the Primary Markets' minimum fixed fees per order (see Section 3.1).

We also report the results for terciles based on stocks' average trading volume. Chi-X has a considerably larger market share (both in terms of trades and traded value) for the most active stocks, which is consistent with the evidence presented in Hengelbrock and Theissen [2009] for the Turquoise MTF.

Panel A of Table 3 contains statistics about the quality of Chi-X's quotes. The MTF is frequently present at the EBBO (around 49% for either bid or ask), and often even improves on the Primary Markets' quotes (ca. 26% for bid or ask). Nevertheless, the frequency with which the MTF is simultaneously present at both sides of the inside quote (alone) is considerably lower with approximately 24% (7%), indicating that the activity on Chi-X is often restricted to one side of the market. While the Primary Markets are naturally present at the inside quote more often, they frequently face competition for at least one side of the market as they only spend roughly 26% of the time alone at the EBBO. Investigating the individual terciles, one can see that the MTF's quote competitiveness is somewhat higher for more active stocks, which is in line with the higher market shares in those stocks.

[Insert Table 3 about here]

Panel B of Table 3 reports the average available market depth for each trading venue conditional on being present at the inside quote. Overall, the available depth in the Primary Markets is roughly three times the depth on Chi-X, which may in part explain the observed cross-market differences with respect to the average trade size. Nevertheless, the MTFs displays considerable depth for its quotes.

Based on its presence at the best quotes, Chi-X's market share (in terms of trades or trading volume) seems strikingly low. This is consistent with the market access friction in our model, which forces captive traders to trade in the Primary Market irrespectively of the quotes prevailing elsewhere. In order to quantify this friction, we follow Foucault and Menkveld [2008], who suggest estimating the proportion of smart routers (θ) by the percentage of trades being executed on Chi-X conditional on the Primary Market offering a *strictly* worse quote. We additionally require that the depth on the MTF is sufficient to get the order filled entirely because it is natural to assume that traders take quantities into account when deciding where to route their orders. Given that Chi-X offers a considerably lower market depth on average, some agents may avoid splitting up their orders and therefore prefer the Primary Market.

This will particularly be the case if the marginally better price on the MTF is only available for a small fraction of the total order size.

The results in Table 4 (first column) strongly confirm the importance of imperfect order routing. Conditional on Chi-X offering a better quote with sufficient depth, every second order is still executed in the Primary Market, such that the proportion of smart routers is roughly 50%. Interestingly, the routing friction varies little across the different activity terciles, which is in contrast to the results in Foucault and Menkveld [2008], who report a marked drop in smart order routing once moving beyond the most active stocks.

[Insert Table 4 about here]

An additional item of great interest is the tie-breaking rule assumed in the theoretical model of Section 2. Given the data at hand, we can actually compute an estimate of the tie-breaking rule, again following Foucault and Menkveld [2008]. In particular, the probability of a trade occurring on the Primary Market conditional on equal quotes across venues and sufficient depth on Chi-X to fill the order completely is equal to

$$\pi = (1-\theta) + \theta\tau$$

where θ is the proportion of smart routers and τ denotes the parameter of the tie-breaking rule. This equation simply states that all captive traders plus a fraction τ of the smart routers will trade on the Primary Market in the case of a tie, while the remaining agents trade on Chi-X. The last two columns of Table 4 contain the estimates for the proportion of trades executing in the Primary Market under an inter-market tie (π) and the tie-breaking rule (τ) for the entire sample as well as the individual terciles. We find that our assumption regarding the tie-breaking rule in Section 2 is clearly confirmed, as we cannot reject the null hypothesis that τ is equal to zero, indicating that smart routers always choose to trade on Chi-X if it at least matches the quotes in the Primary Market. Given that Chi-X charges lower fees for market orders (except for very large orders), this result is not very surprising.

4. Estimating differences in informed trading

The implications of our model from Section 2 regarding market co-existence crucially depend on whether or not informed traders are more likely than noise traders to have access to the alternative trading platform (i.e. Chi-X). It is important to notice, that traders' routing abilities directly translate into the adverse selection risk faced by market makers and the price impact of trades. We can therefore filter out the relevant case for our setting by testing for differences in informed trading between Chi-X and the Primary Markets.

4.1 Effective spread decomposition

One of the most widely used measures for the assessment of trading costs is the percentage effective half-spread, which is defined as

$$ES_t = q_t \frac{p_t - m_t}{m_t} \tag{2}$$

where p_t denotes the transaction price at time t, m_t is the contemporaneously prevailing EBBO mid-quote, and q_t is a trade direction indicator that takes the value of 1 for buys and -1 for sells. Compared to the quoted spread, this measure has the advantage that it measures trading costs only at the actual time of a trade, taking into account that liquidity demanders will attempt to time the market and trade when the bid-ask spread is relatively narrow.

Besides its simplicity, this measure has the additional advantage that it can be decomposed into an adverse selection (price impact) component

$$AS_t = q_t \frac{m_{t+\Delta t} - m_t}{m_t} \tag{3}$$

and an order processing component, usually termed realized half-spread

$$RS_t = q_t \frac{p_t - m_{t+\Delta t}}{m_t} \qquad (4)$$

where $m_{t+\Delta t}$ is the mid-quote Δt minutes after the transaction, the time at which the market maker is assumed to cover her position. While these measures constitute extreme simplifications of reality (e.g. trades between t and t+ Δt are ignored), they have become a benchmark for assessing trading costs. Moreover, this spread decomposition also allows us to compare market maker revenues before transaction fees across markets through the realized spread.

For both markets, we calculate all three measures for each stock and trading day and then calculate averages across stock-days for the separate activity terciles. Given that even the least active stocks in our sample have a considerable trading volume, this procedure delivers relatively conservative standard errors. Moreover, trade-weighted statistics would bias the results in favour of Chi-X, as it has a larger market share in the most active stocks, which generally exhibit lower effective spreads. In all calculations, we exclude trades that occur when the market is locked or crossed, i.e. when the EBBO spread is non-positive (see Shkilko et al. [2008]). Nevertheless, including these observations does not alter the results qualitatively.

The results are listed in Table 5. Overall, trading on Chi-X is not cheaper before fees: Across all stocks and days, the effective spread on Chi-X averages 2.67 bps, compared to 2.64 bps in the Primary Market (Panel A). The difference of 0.03 bps is very small in economic terms (roughly 1%) and statistically insignificant. Given that Chi-X charges lower fees for market orders (except for very large trade sizes, see Section 3.1), the difference in effective spreads can be expected to be slightly negative net of fees. Exact calculations are not possible because participants in the Primary Markets may be granted rebates depending on their trading activity. Overall, the results suggest that trading on Chi-X is at most marginally cheaper than on the Primary Markets net of fees.

[Insert Table 5 about here]

Nevertheless, a look at the spread decomposition[7] (Panels B and C) reveals important differences between both markets. Chi-X displays a significantly larger adverse selection component (2.68 bps compared to 2.27 bps), but markedly lower realized spreads (-0.01 bps vs. 0.37 bps). Importantly, the differences are both statistically and economically very significant. Liquidity providers on Chi-X are exposed to a much greater adverse selection risk, while their gross revenues are essentially equal to zero. Nevertheless, as Chi-X grants a 0.2 bps rebate per executed limit orders, they still net a small profit after fees. Given that liquidity providers on the Primary Markets face a positive transaction fee[8], market makers' revenues appear to be very similar across markets. Additionally, the fact that revenues from liquidity provision are very close to zero indicates a very competitive market.

Overall, the effective spread decomposition clearly suggests that liquidity providers on Chi-X face a higher adverse selection risk. This result appears very robust as it holds across all activity terciles, and we observe a higher price impact on Chi-X for all but 3 stocks[9] (these negative differences are not statistically different from zero). Moreover, the realized spreads nicely illustrate that the liquidity rebate on the MTF helps market makers to sustain this excess risk.

In our model, cross-market differences in adverse selection risk arise because the proportion of informed traders differs between smart routers and captive traders. While a higher price impact for orders executed on Chi-X indicates that smart routers are more likely than captive traders to be informed ($\theta^I > \theta^U$ or equivalently $\mu^{SR} > \mu$), it also implies that we should observe a lower price impact for trade-throughs, as those stem exclusively from less informed captive traders ($\mu^{CT} < \mu$). In order to verify this, we separate the Primary Market trades into trade-throughs and non-trade-throughs and calculate the effective spread decomposition for both types of transactions.

[Insert Table 6 about here]

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[7] We set Δt = 5 minutes. Setting the interval to 15 or 30 minutes delivers qualitatively similar results.
[8] Except for designated market makers.
[9] For the sake of parsimony, we do not report the results for individual stocks (available upon request).

The results in Table 6 strongly confirm that trades violating inter-market price priority are more likely to stem from uninformed traders than transactions that occur while the Primary Market is at the inside quote. The estimated average price impact of a trade-through is 0.91 bps, which is less than half of the 2.39 bps price impact of non-trade-throughs. Naturally, trade-throughs display a significantly larger effective spread (4.53 bps), as they leave money on the table by trading through a better available quote. Paired with the lower price impact, this boosts the realized spread (3.62 bps), which is pocketed by the market maker. Overall, these results indicate that the observed excess adverse selection risk on Chi-X is driven by the absence of mainly uninformed captive traders.

4.2 Hasbrouck's structural VAR

In a seminal contribution, Hasbrouck [1991] suggests a structural VAR model to estimate the permanent price impact of a trade. Since then, this measure has emerged as one of the most frequently employed procedures in the empirical market microstructure literature. The basic idea behind Hasbrouck's model is that there exists a dynamic linear relationship between price (quote) changes and trades, where current trades have an impact on current *and* future price changes, while current price changes can only trigger future trades. In our context, the model can be written as

$$r_t = \sum_{i=1}^{K} a_i r_{t-i} + \sum_{i=0}^{K} b_i x_{t-i}^{P} + \sum_{i=0}^{K} c_i x_{t-i}^{C} + \varepsilon_t^{r} \tag{5}$$

$$x_t^{P} = \sum_{i=1}^{K} d_i r_{t-i} + \sum_{i=1}^{K} e_i x_{t-i}^{P} + \sum_{i=1}^{K} f_i x_{t-i}^{C} + \varepsilon_t^{P} \tag{6}$$

$$x_t^{C} = \sum_{i=1}^{K} g_i r_{t-i} + \sum_{i=1}^{K} h_i x_{t-i}^{P} + \sum_{i=1}^{K} i_i x_{t-i}^{C} + \varepsilon_t^{C} \tag{7}$$

where r_t denotes log changes in the EBBO mid-quote and the $x_t^k,\ k \in \{P,C\}$ are discrete variables that take the value of 1 for a buy, -1 for a sell, and 0 otherwise. As detailed by Hasbrouck [1991], the discrete nature of the x_t^k does not constitute any obstacle for the structural VAR. We estimate the model in tick time, such that trades across markets are necessarily uncorrelated[10], and truncate the VAR after 10 lags[11]. At the beginning of each trading day, all lags are set to zero. To judge the long-term (permanent) price impact of a trade, the VAR is inverted to obtain the VMA representation

$$\begin{pmatrix} r_t \\ x_t^P \\ x_t^C \end{pmatrix} = \begin{pmatrix} A(L) & B(L) & C(L) \\ D(L) & E(L) & F(L) \\ G(L) & H(L) & I(L) \end{pmatrix} \begin{pmatrix} \varepsilon_t^r \\ \varepsilon_t^P \\ \varepsilon_t^C \end{pmatrix} \tag{8}$$

where A(L) – I(L) are lag polynomials. This is the impulse response function, and the long-term price responses to an unexpected trade in either market are given by the coefficient sums $PI^P = \sum_{i=0}^{\infty} B_i$ and $PI^C = \sum_{i=0}^{\infty} C_i$.

[Insert Table 7 about here]

Table 7 contains the permanent price impacts for both markets (impulse responses are truncated after 20 periods), where we again report stock-day averages for the entire sample and the activity terciles. The results are in line with those from the effective spread decomposition. On average, the permanent price impact of a trade on Chi-X amounts to 1.86 bps, compared to 1.61 bps for Primary Market trades. The difference is statistically significant at the 1% level. As in the previous section, we observe a higher price impact on Chi-X for each activity tercile, which underlines the robustness of our findings. For individual stocks, we find a higher price impact for Primary market trades in only 6 cases, and none of these differences are statistically significant[12]. Overall, these results provide further evidence for liquidity providers facing a higher adverse selection risk on Chi-X.

In order to check whether the difference in adverse selection across markets is indeed due to captive traders being mainly uninformed, we modify the VAR from equations

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[10] Estimating the model with data aggregated to 5-second intervals delivers qualitatively similar results but requires placing upper and lower bounds on a venue's price impact as the order flows are no longer uncorrelated.

[11] The inclusion of additional lags does not alter our conclusions.

[12] The results for individual stocks, which we do not report for brevity, are available upon request.

(5) – (7) and split the Primary Market order flow into trade-throughs and non-trade-throughs. This results in the following VAR system

$$r_t = \sum_{i=1}^{K} a_i r_{t-i} + \sum_{i=0}^{K} b_i x_{t-i}^{P,NTT} + \sum_{i=0}^{K} c_i x_{t-i}^{P,TT} + \sum_{i=0}^{K} d_i x_{t-i}^{C} + \varepsilon_{r,t} \tag{9}$$

$$x_t^{P,NTT} = \sum_{i=1}^{K} e_i r_{t-i} + \sum_{i=1}^{K} f_i x_{t-i}^{P,NTT} + \sum_{i=1}^{K} g_i x_{t-i}^{P,TT} + \sum_{i=1}^{K} h_i x_{t-i}^{C} + \varepsilon_{NTT,t} \tag{10}$$

$$x_t^{P,TT} = \sum_{i=1}^{K} i_i r_{t-i} + \sum_{i=1}^{K} j_i x_{t-i}^{P,NTT} + \sum_{i=1}^{K} k_i x_{t-i}^{P,TT} + \sum_{i=1}^{K} l_i x_{t-i}^{C} + \varepsilon_{TT,t} \tag{11}$$

$$x_t^{C} = \sum_{i=1}^{K} m_i r_{t-i} + \sum_{i=1}^{K} n_i x_{t-i}^{P,NTT} + \sum_{i=1}^{K} o_i x_{t-i}^{P,TT} + \sum_{i=1}^{K} p_i x_{t-i}^{C} + \varepsilon_{C,t} \tag{12}$$

where $x_{t-i}^{P,TT}$ and $x_{t-i}^{P,NTT}$ refer to Primary Market order flow due to trade-throughs and non-trade-throughs, respectively. Table 8 reports the permanent price impacts obtained from the corresponding VMA representation. The results are qualitatively similar to those obtained from the effective spread decomposition. The permanent price impact of a trade-through is 0.44 bps, which is significantly lower than 1.72 bps impact of a non-trade-through, with a t-statistic of around 15. This supports the view that market makers on Chi-X face a higher adverse selection risk precisely because their quotes are not exposed to the relatively uninformed captive traders.

[Insert Table 8 about here]

4.3 PIN

Given our theoretical framework, the PIN model by Easley et al. [1996b] is a natural choice for assessing differences in informed trading between Chi-X and the Primary Markets. Nevertheless, a number of recent papers (e.g. Duarte and Young [2009] and Aktas et al. [2007]) have cast doubt on the model's ability to capture the presence of informed traders. Moreover, it is well-known that the PIN model is subject to numerical problems, particularly for stocks with high trading activity (see e.g. Yan and Zhang [2009] and Easley et al. [2010]). In our case, these problems are additionally amplified by the relatively short sample (43 trading days) and the need to estimate additional parameters for a two-market PIN model as in Easley et al. [1996a]

or Grammig et al. [2001]. Consequently, we find that the numerical maximization of the likelihood function is not successful for most stocks in our sample. In Appendix C, we provide an alternative method for estimating differences in informed trading between two markets via the PIN model and present the associated results.

5. Differences in adverse selection and Chi-X's quote competitiveness

The results of the previous section suggest that trades on Chi-X carry more private information than those executing place in the Primary Markets. From the perspective of our theoretical model, this corresponds to the case where informed traders have a higher likelihood of being smart routers than captive traders (i.e. $\theta^I > \theta^U$ or equivalently $\mu^{SR} > \mu$). Recall from the discussion of Proposition 1 in Section 2 that in this case, liquidity providers on Chi-X are only able to match the primary market's quotes if their cost advantage from transaction fees (c) exceeds the excess adverse selection risk they face.

In order to validate our model empirically, we adopt a cross-sectional perspective. According to Corollary 1, Chi-X's presence at the inside quote is expected to decrease (weakly) in the adverse selection risk differential. As the empirical evidence suggests that the adverse selection risk differential is positive for almost all stocks, we actually expect to observe a strictly negative relationship.

We begin by calculating, for each stock, the fraction of time during which Chi-X is present at the EBBO, taking the average of both sides of the market[13]. We then regress this measure of Chi-X's quote competitiveness on measures that capture the difference in adverse selection across trading venues and additional control variables, i.e. we estimate the cross-sectional regression

$$Chi\_at\_best_i = \alpha_0 + \alpha_1 1_{[Euronext]} + \gamma(\Delta AS_i) + \phi' X_i + \varepsilon_i \qquad (13)$$

[13] Considering only one side of the market (either bid or ask) delivers qualitatively similar results.

where $1_{[Euronext]}$ is an indicator variable that takes the value of 1 if the stock is listed on Euronext and 0 otherwise, ΔAS_i denotes the excess adverse selection risk on Chi-X for stock i, and X_i is a vector of control variables.

We employ three different variables in order to quantify the excess adverse selection risk on Chi-X. The first two are the stock-specific cross-market differences of the price impact measures from Sections 4.1 and 4.2, denoted ΔAS_i^{SD} and ΔAS_i^{HB}, respectively. For the third variable, we ignore any cross-sectional variation in the proportion of informed traders and simply proxy $(\mu^{SR} - \mu)(\overline{V} - \underline{V})$ by σ_i, which denotes annualized return volatility based on closing prices for the calendar year prior to our sample period. Table 9 in the appendix contains the cross-sectional correlation matrix of our three explanatory variables. Unsurprisingly, we find a strong cross-sectional correlation of 0.63 between ΔAS_i^{SD} and ΔAS_i^{HB}. More interestingly, both measures are highly correlated with stock price volatility (between 0.42 and 0.45), which indicates that all three variables are picking up similar effects.

[Insert Table 9 about here]

We include a number of control variables that we expect to influence Chi-X's presence at the best quote.

While we have not incorporated the effect of tick sizes in our model for tractability reasons, it is known that a discrete pricing grid leads to rounding errors and therefore artificially inflates the bid-ask spread (see e.g. Harris [1994]). As a consequence, we expect Chi-X's quote competitiveness to increase in the tick size differential[14], which we define as the average[15] difference in tick sizes (Primary market minus Chi-X) for stock i scaled by the stock's average transaction price. We furthermore include the proportion of smart routers as a control variable in order to disentangle our story from

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[14] For some stocks, the difference in tick sizes is considerable. For example, during most of the sample, the tick size for Infineon is €0.01 on Xetra, compared to €0.001 on Chi-X. Given the stock's low price level (below €10), the bid-ask spread on the Primary Market is frequently equal to the tick size. Consequently, Chi-X is particularly attractive for trading in this stock as it allows the placement of orders within the primary quotes. A few days before the end of the sample period, Deutsche Börse reduced the tick size to €0.005.

[15] A total of 9 stocks experience a change in tick sizes during our sample period, all of them corresponding to a reduction in the Primary Market tick size. One stock (STMicroelectronics) experiences two changes.

that of Foucault and Menkveld (2008). Additionally, we also control for the log of trading volume and a stock's return synchronicity (based on the R-Square of a market model regression[16]). While trading volume is simply a variable outside our model, the results in Theissen and Hengelbrock (2009) suggest that trading in more active stocks has a higher tendency to fragment. Return synchronicity may capture effects of algorithmic traders, which often engage in index arbitrage trades and have been shown to be particularly quick in reacting to "hard" information (Jovanovic and Menkveld [2010]).

[Insert Table 10 about here]

The coefficient estimates are listed in Table 10 in the Appendix. As predicted by our model, the results indicate that an increase in the adverse selection risk differential is associated with Chi-X being less frequently at the inside quote. The coefficients on ΔAS_i^{SD}, ΔAS_i^{HB} and σ_i are all negative and strongly significant (t-statistics ranging from 3.3 to 8.2). Importantly, the observed effects are also economically important. For example, a one standard deviation increase in ΔAS_i^{SD} (~0.37 bps) is associated with a decrease of around 4.35% in Chi-X's presence at the inside quote. The other variables have marginal effects of similar magnitude (7.07% and 3.95% for ΔAS_i^{HB} and σ_i, respectively)

All control variables carry the expected sign. Particularly the difference in tick sizes across venues plays an important role for Chi-X's quote competitiveness. Increasing the tick size differential by one standard deviation (~2.2 bps) leads Chi-X's presence at the best quote to increase by 7-11%, depending on the specification. Different from Menkveld and Foucault [2008], we find that the proportion of smart routers is not significantly related to Chi-X's quote competitiveness. This is likely due to the fact that exchanges do not charge any fees for order submission, which is an important feature of their model and data. For the other control variables, we find that both higher trading volume and higher return synchronicity are associated with Chi-X being at the inside quote more frequently. Finally, there is some weak evidence for

[16] We use the transformation $SYNCH = \ln(R^2/(1-R^2))$, see e.g. Teoh et al. [2008]. Market model regressions are estimated using 1 year of daily data prior to our sample period.

Chi-X offering worse quotes in stocks listed on Euronext. This may be due to the staggered entry of the MTF across countries. While Chi-X entered the German market roughly one year before the start of our sample period, it did not offer trading in French stocks until half a year later.

While our theoretical model is strictly speaking about quotes, it has very similar implications regarding Chi-X's actual market share. Given a fixed number of trading rounds, a higher excess adverse selection risk leads to less trade on Chi-X after controlling for the proportion of smart routers. We therefore re-estimate equation (12), but replace Chi-X's presence at the best quote with the MTF's market share in terms of trades. The results (Table 11) are very similar than the results for quotes. All variables capturing the adverse selection risk differential are negative and statistically significant. Again, the economic effects are substantial. For example, a one standard deviation increase in ΔAS_i^{SD} is associated with an increase of 1.10% in Chi-X's market share. Unsurprisingly, the explanatory effect of the proportion of smart routers is strongly significant. The coefficients on the remaining control variables are, by and large, similar to the results using Chi-X's presence at the inside quote.

[Insert Table 11 about here]

Overall, the cross-sectional evidence suggests that Chi-X's competitiveness is significantly hampered by excess adverse selection risk. These findings strongly support our theoretical model.

6. Conclusion

Motivated by the current regulatory framework in Europe set forth under MiFID, we analyze how adverse selection risk and transaction fees interact in a fragmented financial market where trade-throughs are not prohibited. We argue that liquidity providers on alternative trading platforms will be subject to an increased adverse selection risk if informed traders are more likely to have access to this market via a smart order routing system. Consequently, the Primary Market will dominate (display better quotes) most of the trading day despite charging higher transaction fees. We formalize this argument with an extension of the Glosten and Milgrom [1985] sequential trade model.

The analysis of a recent sample of transactions and quote data for German and French stocks reveals that liquidity providers on Chi-X (a recently launched trading platform) face a significantly greater adverse selection risk. Moreover, trade-throughs that execute “by default” in the Primary Markets are particularly uninformed. In line with our theoretical model, we find a negative relationship between the excess adverse selection risk and Chi-X’s presence at the inside quote. Moreover, our view is additionally supported by anecdotal evidence from Primary Market outages.

Our findings have some implications for the design of best execution policies. Allowing for trade-throughs favors the Primary Markets by ensuring that the least informative order flow does not reach the MTFs, thereby hampering liquidity provision on these platforms due to an increased adverse selection risk. Our findings suggest that protecting orders from trade-throughs in the spirit of RegNMS may foster competition between trading venues as it helps to level the playing field.

There are some interesting avenues for future research. In our theoretical analysis, we have taken exchanges’ transaction fees and investors’ routing technologies as given. This choice follows from noise traders’ willingness to trade at any price and the assumption that agents do not have the chance to trade multiple times. Clearly, a more realistic model would aim to determine these variables endogenously.

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Appendix A: Proof of Proposition 1

Before we state the proof of Proposition 1, it is useful to introduce some additional notation.

As trader populations differ across markets, so does the function that maps market makers (henceforth MMs) prior into their posterior beliefs. Let $\delta_t(sell_t, \delta_{t-1})$ denote the posterior belief about the probability of a high realization of the liquidation value after a sell by the t-th trader, given the prior δ_{t-1}. Then, using Bayes' rule,

$$\delta_t(sell_t, \delta_{t-1}) = \frac{(1-\mu)\delta_{t-1}}{1+\mu(1-2\delta_{t-1})} \qquad \text{if sell in } P \text{ and } b_t^P > b_t^C \qquad (A.1)$$

$$\delta_t(sell_t, \delta_{t-1}) = \frac{(1-\mu^{CT})\delta_{t-1}}{1+\mu^{CT}(1-2\delta_{t-1})} \qquad \text{if sell in } P \text{ and } b_t^P \le b_t^C \qquad (A.2)$$

$$\delta_t(sell_t, \delta_{t-1}) = \frac{(1-\mu^{SR})\delta_{t-1}}{1+\mu^{SR}(1-2\delta_{t-1})} \qquad \text{if sell in } C \qquad (A.3)$$

From this follows that the expected liquidation value of the asset conditional on the arrival of a sell order is given by

$$B(\mu, \delta_{t-1}) \equiv E(V \mid sell, \delta_{t-1}) = \frac{(1-\mu)\delta_{t-1}\overline{V} + (1+\mu)(1-\delta_{t-1})\underline{V}}{(1+\mu(1-2\delta_{t-1}))} \qquad \text{if sell in } P \text{ and } b_t^P > b_t^C \qquad (A.4)$$

$$B(\mu^{CT}, \delta_{t-1}) \equiv E(V \mid sell, \delta_{t-1}) = \frac{(1-\mu^{CT})\delta_{t-1}\overline{V} + (1+\mu^{CT})(1-\delta_{t-1})\underline{V}}{(1+\mu^{CT}(1-2\delta_{t-1}))} \qquad \text{if sell in } P \text{ and } b_t^P \le b_t^C \qquad (A.5)$$

$$B(\mu^{SR}, \delta_{t-1}) \equiv E(V \mid sell, \delta_{t-1}) = \frac{(1-\mu^{SR})\delta_{t-1}\overline{V} + (1+\mu^{SR})(1-\delta_{t-1})\underline{V}}{(1+\mu^{SR}(1-2\delta_{t-1}))} \qquad \text{if sell in } C \qquad (A.6)$$

Clearly, $\mu^{SR} > \mu > \mu^{CT}$ ($\mu^{SR} < \mu < \mu^{CT}$) implies $B(\mu^{CT}, \delta_{t-1}) \ge B(\mu, \delta_{t-1}) \ge B(\mu^{SR}, \delta_{t-1})$ ($B(\mu^{CT}, \delta_{t-1}) \le B(\mu, \delta_{t-1}) \le B(\mu^{SR}, \delta_{t-1})$), where equality applies to the limiting cases of $\delta_{t-1} = 0$ and $\delta_{t-1} = 1$.

We are now ready to state the proof of Proposition 1. For notational simplicity, we omit the time subscripts on MMs beliefs.

Proof of Proposition 1:

Part A: $\theta^I > \theta^U$

Case A1: $B(\mu,\delta) - c > B(\mu^{SR},\delta)$

In this case, $b_t^{i,P}* = B(\mu,\delta) - c$ for i=1,…, N^P and $b_t^{j,C}* < b_t^P*$ for j=1,…, N^C constitutes a Nash equilibrium. All trade occurs in market P, and MMs obtain zero expected profits in both markets. Unilaterally decreasing the bid in market P does not improve on zero expected profits, as such a quote does not attract any market order, given the other MMs quote. On the other hand, $B(\mu,\delta) - c$ is the maximum bid that does not lead to expected losses, thereby ruling out any unilateral increases in the quote. Concerning market C, any bid $b_t^{j,C} \geq B(\mu,\delta) - c$ will yield an expected loss for market maker j as the expected liquidation value conditional on the sell of a smart router is $B(\mu^{SR},\delta) < B(\mu,\delta) - c$. Lowering the bid unilaterally does not improve on zero expected profits.

To see that we must have $b_t^P* > b_t^C*$ in equilibrium, first consider the case where $b_t^P* < b_t^C*$. Clearly, equilibrium requires $b_t^C* \leq B(\mu^{CT},\delta)$. Given $b_t^P* < b_t^C*$, market makers in market P make expected profits. Thus for every $b_t^P* < b_t^C*$, there exists some $b_t^{i,P} = b_t^P* + \varepsilon < b_t^C*$ that allows market maker i to overbid her rival in the same market and thereby increase her profits. Hence, this cannot be an equilibrium. Now consider the situation where $b_t^P* = b_t^C*$. Given that MMs in market P (C) face proportions μ^{CT} (μ^{SR}) of informed traders, we must have $b_t^P* \leq B(\mu^{CT},\delta) - c$ and $b_t^C* \leq B(\mu^{SR},\delta)$ and therefore $b_t^P* \leq B(\mu^{SR},\delta)$. By symmetry, we have $b_t^{i,P}* = b_t^P*$ and $b_t^{j,C}* = b_t^C*$ for i=1,…, N^P and j=1,…, N^C. If $b_t^P* = b_t^C* < B(\mu^{SR},\delta)$, then market maker j in market C can capture the market by posting $b_t^{j,C} = b_t^C* + \varepsilon$, such that this is not an equilibrium. On the other hand, if $b_t^P* = b_t^C* = B(\mu^{SR},\delta)$, market maker i in market P makes an expected profit equal to $\Pi = (1-\theta)(B(\mu^{CT},\delta) - B(\mu^{SR},\delta) - c)/N^P > 0$. Increasing her bid marginally to $b_t^{i,P} = B(\mu^{SR},\delta) + \varepsilon < B(\mu,\delta) - c$, her profit is equal to $B(\mu,\delta) - B(\mu^{SR},\delta) - c - \varepsilon$, which is always greater than Π for $N^P \to \infty$.

Case A2: $B(\mu^{CT},\delta)-c \geq B(\mu^{SR},\delta) \geq B(\mu,\delta)-c$

For this case, $b_t^{j,C}* = b_t^{i,P}* = B(\mu^{SR},\delta)$ for i=1,…,N^P and j=1,…,N^C is a Nash equilibrium. Given our assumption regarding inter-market ties, smart routers trade in market C and captive traders in market P. MMs in market C earn zero expected profits and MMs in market P make expected profits as $B(\mu^{CT},\delta)-c-B(\mu^{SR},\delta) \geq 0$. Unilaterally decreasing any bid leads to zero profits, as it attracts no market order, given the other quotes. On the other hand, a unilateral increase in the bid quote in market P (C) generates expected losses as such a quote then faces a proportion μ (μ^{SR}) of informed traders.

To see that any equilibrium must satisfy $b_t^C* = b_t^P*$, first assume that $b_t^C* > b_t^P*$. Clearly, we must have that $b_t^C* = B(\mu^{SR},\delta)$. Given the quotes in market C, market makers in market P face a proportion μ^{CT} of informed traders. As long as $b_t^C* > b_t^P*$, there always exists some $b_t^{i,P} = b_t^P* + \varepsilon < b_t^C*$ that allows market maker i to overbid her rivals in the same market and thereby increase her profits. Hence, this cannot be an equilibrium. Now consider the converse situation, i.e. $b_t^P* > b_t^C*$. Given that market P displays the best quotes across markets, the adverse selection risk is defined by a proportion μ of informed traders, such that we must have $b_t^P* = B(\mu,\delta)-c$. But then, market maker j in market C faces a proportion μ^{SR} of informed traders, such that she can obtain an expected profit by increasing her bid to $b_t^{j,C} = B(\mu,\delta)-c$. Hence, this cannot an equilibrium either.

Case A3: $B(\mu^{SR},\delta) > B(\mu^{CT},\delta)-c$

Under this constellation, $b_t^{i,P}* = B(\mu^{CT},\delta)-c$ and $b_t^{j,C}* = B(\mu^{SR},\delta)$ for i=1,…,N^P and j=1,…,N^C constitutes a Nash equilibrium. Smart routers trade in market C, captive traders in market P, and all MMs obtain zero expected profits. Unilaterally lowering a bid quote in either does not attract any market orders, given the other quotes. Increasing the quote in market P leads to expected losses because such a quote faces proportions μ^{CT} (if $b_t^{i,P} \in (B(\mu^{CT},\delta)-c, B(\mu^{SR},\delta)]$) or μ (if $b_t^{i,P} > B(\mu^{SR},\delta)$) of informed traders. Similarly, higher bid quotes in market C lead to expected losses as the expected liquidation value conditional on a sell order in market C is equal to $B(\mu^{SR},\delta)$.

To see that we must have $b_t^C* > b_t^P*$ in equilibrium, first consider the case where $b_t^C* < b_t^P*$. Under this constellation, markets makers in market P face a proportion μ of informed traders and equilibrium requires that $b_t^P* = B(\mu,\delta) - c$. As in the previous case, market maker j in market C can make an expected profit by posting $b_t^{j,C}* = B(\mu,\delta) - c$, such that this is not an equilibrium. Now suppose that $b_t^C* = b_t^P*$. Clearly, we must have that $b_t^P* \leq B(\mu^{CT},\delta) - c$, because any higher bid in market P will lead to losses given a proportion μ^{CT} of informed traders. But then, any market maker j in market C has an incentive to increase her bid marginally to some $b_t^{j,C} = b_t^C* + \varepsilon$, thereby capturing the market and increasing her profits.

Combining cases A1-A3, we find that $b_t^C* \geq b_t^E*$ if and only if $B(\mu^{SR},\delta) \geq B(\mu,\delta) - c$. Using equations (A.4) and (A.6), the market co-existence condition (1) follows.

Part B: $\theta^U \geq \theta^I$

In this case, the inequality $B(\mu^{SR},\delta) > B(\mu^{CT},\delta) - c$ is always satisfied because $\mu^{SR} < \mu^{CT}$. It follows from case A3 that we must have $b_t^{j,C}* = B(\mu^{SR},\delta)$ for j=1,…, N^C and $b_t^{i,P}* = B(\mu^{CT},\delta) - c$ for i=1,…, N^P in equilibrium, such that markets co-exist. Condition (1) is satisfied because $\mu^{SR} - \mu < 0$.

Q.E.D.

Appendix B: Tables and Figures

Table 1: Sample Stocks

This Table contains a list of the 67 French and German stocks contained in our sample, separated into terciles based on their average trading volume (in €).

High Volume Stocks (N=22)	Medium Volume Stocks (N=23)	Low Volume Stocks (N=22)
Total	Carrefour	Postbank
Deutsche Bank	BMW	Linde
Allianz	Deutsche Post	Michelin
Siemens	Vivendi	Bouygues
Daimler	ThyssenKrupp	Pernod Ricard
E.ON	Credit Agricole	Alcatel Lucent
Societe Generale	EDF	PPR
BNP Paribas	Lafarge	Accor
Deutsche Telekom	Renault	Adidas
France Telecom	Schneider	Cap Gemini
RWE	Vallourec	Gaz de France
Volkswagen	L'Oreal	STMicroelectronics
AXA	Veolia	Merck
SAP	Lufthansa	Metro
Bayer	Danone	Unibail Rodamco
BASF	LVMH	Hypo Real Estate
Deutsche Börse	MAN	Air France - KLM
Suez	Alstom	Henkel
Munich Re	Saint Gobain	TUI
Sanofi Synthelabo	Vinci	Fresenius Medical Care
Continental	Peugeot	Essilor
Commerzbank	Air Liquide	Lagardere
	Infineon	

Table 2: Sample Statistics

This Table contains summary statistics of the trading activity on Chi-X and the Primary Markets for our sample of 67 French and German stocks, aggregated into terciles based on trading activity. MS Chi-X denotes the market share of Chi-X for trades and trading volume as a percentage of the consolidated market (Chi-X plus primary market). Ratio C/E denotes the average trade size on Chi-X as percentage of the average trade size in the Primary Market.

Panel A: Avg. daily # of trades (1,000 trades)			
	Chi-X	Primary	MS Chi-X (%)
High Volume	1.06	5.85	14.98
Medium Volume	0.52	3.99	11.47
Low Volume	0.30	2.59	10.52
All	0.63	4.14	12.31
Panel B: Avg. daily trading volume (Mio. €)			
	Chi-X	Primary	MS Chi-X (%)
High Volume	18.33	244.31	6.99
Medium Volume	5.83	96.85	5.53
Low Volume	2.96	51.54	5.36
All	8.99	130.39	5.95
Panel C: Average trade size (€1,000)			
	Chi-X	Primary	Ratio C/P (%)
High Volume	17.38	42.26	41.82
Medium Volume	10.99	24.86	43.63
Low Volume	9.55	20.04	47.94
All	12.62	28.99	44.45

Table 3: Quote competitiveness and market depth

This table contains statistics on the quote competitiveness and the available market depth for our sample of 67 French and German stocks, aggregated into terciles based on trading activity and reported separately for Chi-X and the Primary Markets. Panel A reports the average frequency with which a given market is present (alone) at the inside quote, while Panel B reports the average market depth (in €10,000) for each market conditional on being present (alone) at the inside quote.

	At best bid	At best ask	At both	At best bid alone	At best ask alone	At both alone
			Panel A: Presence (%) at the inside quote			
			Chi-X			
High Volume	52.65	53.56	27.45	27.75	28.18	7.11
Medium Volume	49.77	48.59	23.84	27.28	25.66	6.54
Low Volume	45.13	45.63	20.98	24.99	23.00	6.21
All	49.30	49.25	24.08	26.68	25.62	6.62
			Primary market			
High Volume	72.25	71.82	51.18	47.35	46.44	21.24
Medium Volume	72.72	74.34	53.59	50.23	51.41	25.48
Low Volume	75.01	77.00	58.22	54.87	54.37	30.22
All	73.32	74.38	54.32	50.81	50.75	25.64
			Panel B: Depth (in €10,000) conditional on presence at the inside quote			
			Chi-X			
High Volume	31.02	31.02	30.64	27.08	27.27	26.94
Medium Volume	17.69	17.53	17.45	16.43	15.51	15.94
Low Volume	14.49	15.29	14.77	14.06	13.29	13.86
All	21.02	21.22	20.90	19.15	18.64	18.88
			Primary market			
High Volume	91.74	102.41	103.04	74.62	87.42	95.70
Medium Volume	50.42	53.35	55.78	43.20	46.94	50.78
Low Volume	39.25	42.46	42.91	35.16	38.28	39.20
All	60.32	65.88	67.07	50.88	57.39	61.73

Table 4: The proportion of smart routers and the tie-breaking rule

This table contains estimates for the proportion of smart routers (θ), the proportion of executions in the Primary Market under inter-market ties (π), as well as for the tie-breaking rule parameter (τ) for our sample of 67 French and German stocks, aggregated into terciles based on trading activity. All variables are defined in Section 3. Standard errors are robust to serial and cross-sectional correlation. The standard errors for the tie-breaking rule parameter are based on the delta method.

	Proportion of smart routers	Proportion of Primary Market Trades under inter-market ties	Tie-breaking rule parameter
High Volume	0.514	0.510	0.046
	(0.018)	(0.022)	(0.035)
Medium Volume	0.495	0.513	0.015
	(0.018)	(0.018)	(0.033)
Low Volume	0.494	0.525	0.039
	(0.020)	(0.027)	(0.041)
All	0.501	0.516	0.033
	(0.013)	(0.015)	(0.025)

Table 5: Effective spread decomposition (Chi-X vs. Primary Market Trades)

This table contains the average effective spreads as well as the decomposition into the adverse selection (price impact) and realized spread components for trades on Chi-X and the Primary Markets, respectively, following equations (2) to (4) in Section 4.1. Averages are based on stock-days and aggregated into terciles based on trading activity. For differences, statistical significance at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively. Standard errors are robust to serial and cross-sectional correlation.

Panel A: Effective Spread			
	Chi-X	Primary	Difference
High Volume	1.999	1.996	0.003
	(0.126)	(0.138)	(0.020)
Medium Volume	2.672	2.705	-0.033
	(0.151)	(0.245)	(0.035)
Low Volume	3.341	3.217	0.124**
	(0.217)	(0.219)	(0.052)
All	2.671	2.640	0.031
	(0.128)	(0.140)	(0.074)
Panel B: Price Impact			
	Chi-X	Primary	Difference
High Volume	2.088	1.628	0.460***
	(0.149)	(0.119)	(0.073)
Medium Volume	2.693	2.306	0.387***
	(0.190)	(0.161)	(0.091)
Low Volume	3.270	2.877	0.393***
	(0.210)	(0.163)	(0.122)
All	2.684	2.271	0.413***
	(0.139)	(0.122)	(0.076)
Panel C: Realized Spread			
	Chi-X	Primary	Difference
High Volume	-0.090	0.367	- 0.457***
	(0.102)	(0.098)	(0.074)
Medium Volume	-0.021	0.399	- 0.419**
	(0.104)	(0.152)	(0.191)
Low Volume	0.071	0.340	-0.269
	(0.114)	(0.158)	(0.168)
All	-0.013	0.369	- 0.382***
	(0.078)	(0.094)	(0.104)

Table 6: Effective spread decomposition (Trade-Throughs vs. Non-Trade-Throughs)

This table contains the average effective spreads as well as the decomposition into the adverse selection (price impact) and realized spread components for both trade-throughs and non-trade-throughs on the Primary Markets, following equations (2) to (4) in Section 4.1. Averages are based on stock-days and aggregated into terciles based on trading activity. For differences, statistical significance at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively. Standard errors are robust to serial and cross-sectional correlation.

Panel A: Effective Spread			
	Non-trade-throughs	Trade-throughs	Difference
High Volume	1.883 (0.135)	3.173 (0.196)	- 1.290*** (0.140)
Medium Volume	2.527 (0.191)	4.659 (0.256)	- 2.132*** (0.152)
Low Volume	3.052 (0.196)	5.762 (0.436)	- 2.710*** (0.294)
All	2.488 (0.122)	4.533 (0.232)	- 2.046*** (0.145)
Panel B: Price Impact			
	Non-trade-throughs	Trade-throughs	Difference
High Volume	1.713 (0.120)	0.804 (0.154)	0.909*** (0.116)
Medium Volume	2.453 (0.200)	0.690 (0.247)	1.763*** (0.171)
Low Volume	2.995 (0.170)	1.253 (0.201)	1.742*** (0.200)
All	2.388 (0.130)	0.912 (0.151)	1.476*** (0.124)
Panel C: Realized Spread			
	Non-trade-throughs	Trade-throughs	Difference
High Volume	0.170 (0.085)	2.369 (0.248)	- 2.199*** (0.242)
Medium Volume	0.074 (0.079)	3.969 (0.286)	- 3.896*** (0.286)
Low Volume	0.057 (0.115)	4.509 (0.484)	- 4.452*** (0.465)
All	0.100 (0.068)	3.621 (0.262)	- 3.521*** (0.247)

Table 7: Permanent Price Impacts (Chi-X vs. Primary Market Trades)

This table contains the average permanent price impact measures obtained from the VAR model in Section 4.2, equations (5) – (7). Averages are based on stock-days and aggregated into terciles based on trading activity. For differences, statistical significance at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively. Standard errors are robust to serial and cross-sectional correlation.

	Chi-X	Primary	Difference
High Volume	1.345	1.128	0.218***
	(0.078)	(0.068)	(0.039)
Medium Volume	1.883	1.610	0.273***
	(0.094)	(0.071)	(0.056)
Low Volume	2.337	2.106	0.232***
	(0.138)	(0.110)	(0.081)
All	1.856	1.614	0.241***
	(0.087)	(0.078)	(0.043)

Table 8: Permanent Price Impacts (Trade-Throughs vs. Non-Trade-Throughs)

This table contains the average permanent price impact measures obtained from the VAR model in Section 4.2, equations (9) – (12). Averages are based on stock-days and aggregated into terciles based on trading activity. For differences, statistical significance at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively. Standard errors are robust to serial and cross-sectional correlation.

	Non-trade-throughs	Trade-throughs	Difference
High Volume	1.208	0.274	0.934***
	(0.071)	(0.064)	(0.071)
Medium Volume	1.745	0.326	1.419***
	(0.113)	(0.091)	(0.114)
Low Volume	2.196	0.725	1.471***
	(0.109)	(0.129)	(0.109)
All	1.717	0.440	1.277***
	(0.083)	(0.087)	(0.085)

Table 9: Correlation matrix of explanatory variables

This table contains the correlation matrix for the explanatory variables capturing the excess adverse selection risk on Chi-X. All variables are described in Section 5. Statistical significance at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	ΔAS(SD)	ΔAS(HB)	σ
ΔAS(SD)	1.000	0.635***	0.424***
ΔAS(HB)		1.000	0.453***
σ			1.000

Table 10: Cross-sectional regressions

This table contains estimates for the linear cross-sectional regression following equation (13). All variables are described in Section 5. Robust standard errors are given in parentheses. Statistical significance at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

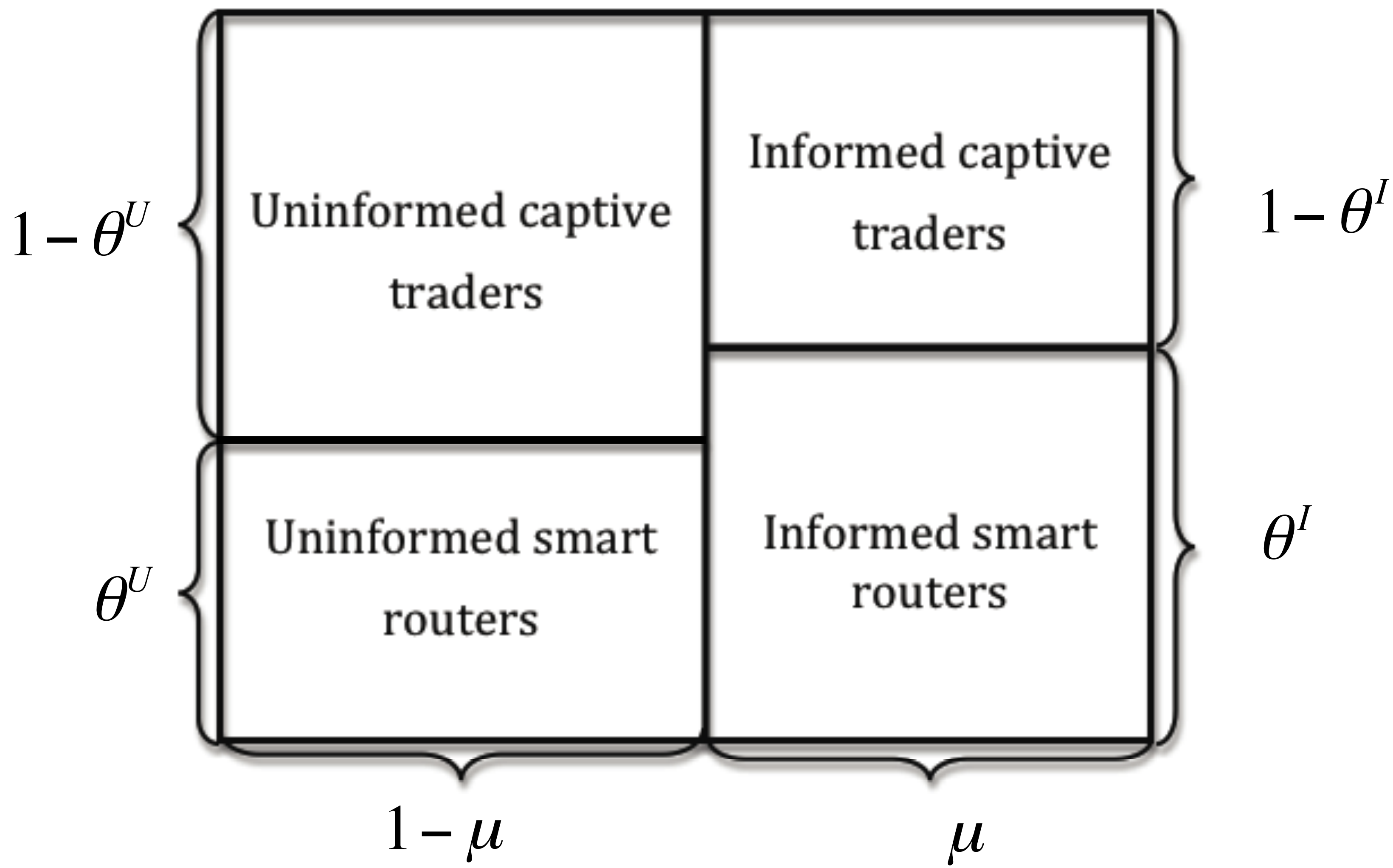
Dependent Variable: Avg. Presence of Chi-X at the best quote			
	(1)	(2)	(3)
ΔAS(SD)	- 11.748***		
	(2.692)		
ΔAS(HB)		- 29.460***	
		(3.606)	
σ			- 0.564***
			(0.169)
% Smart Routers	0.092	-0.095	0.040
	(0.175)	(0.152)	(0.185)
ln(Volume)	7.176***	8.253***	5.267***
	(1.304)	(1.162)	(1.339)
Synch	3.406**	2.288**	4.847***
	(1.409)	(1.007)	(1.616)
Δtick (bps)	4.044***	4.705***	3.449***
	(0.790)	(0.460)	(0.750)
Euronext dummy	-2.280	2.863	-2.624
	(1.915)	(1.726)	(1.967)
Constant	- 86.932***	- 99.333***	-34.504
	(27.592)	(20.508)	(30.037)
N	67	67	67
Adj. R^2	0.606	0.733	0.580

Table 11: Cross-sectional regressions

This table contains estimates for the linear cross-sectional regression following equation (13), where we replace the independent variable by Chi-X's market share in terms of trades. All variables are described in Section 5. Robust standard errors are given in parentheses. Statistical significance at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

Dependent Variable: Avg. Market Share Chi-X (# of Trades)			
	(1)	(2)	(4)
ΔAS(SD)	- 2.989*** (1.091)		
ΔAS(HB)		- 6.997*** (1.862)	
σ			- 0.137** (0.059)
% Smart Routers	0.318*** (0.059)	0.273*** (0.056)	0.305*** (0.061)
ln(Volume)	2.491*** (0.419)	2.735*** (0.403)	2.020*** (0.419)
Synch	1.390** (0.549)	1.106** (0.500)	1.726*** (0.575)
Δtick (bps)	1.094*** (0.271)	1.235*** (0.217)	0.939*** (0.244)
Euronext dummy	- 3.472*** (0.748)	- 2.232*** (0.827)	- 3.542*** (0.757)
Constant	- 47.826*** (8.668)	- 50.598*** (7.702)	- 34.990*** (9.344)
N	67	67	67
Adj. R^2	0.588	0.643	0.572

Figure 1: Graphical representation of the trader population for the case $\theta^I > \theta^U$



Appendix C: A two-market PIN model using regression

As maximum likelihood estimation of the PIN model has become increasingly difficult, Easley et al. [2009] point out that that PIN can be approximated by

$$PIN^{Approx} = \frac{E(|I|)}{E(B+S)} \qquad (C.1)$$

where B and S denote the number of buys and sells, and I=B-S is the order imbalance. The intuition behind this approximation is straightforward. Total order flow is the sum of informed and uninformed trades, while the order imbalance is entirely attributable to informed trades. As a result, PIN can be approximated by the average imbalance divided by the average number of trades.

In our case, unfortunately, it is not sufficient to simply calculate this approximation for each market in isolation, as this would not impose equal event probabilities across markets. A two-market PIN model implies that the order imbalance in each market has the same sign (in expected terms), and the relative order imbalance is higher in the market with a larger proportion of informed traders. Let I_t^k denote the order imbalances in market $k \in \{C,P\}$ on day t, such that the imbalance in the consolidated market is given by $I_t^T = I_t^C + I_t^P$. Moreover define venue k's market share as $S_t^k = (B_t^k + S_t^k)/(B_t^T + S_t^T)$, where the superscript T refers to the consolidated (total) market. Then, the product $I_t^T S_t^k$ is the expected order imbalance in market k in the case where the probability of informed trading in this market is equal to the probability of informed trading in the consolidated market.

Then, we can test for differences in informed trading across venues via the simple linear regression

$$I_t^k = \lambda^k (I_t^T S_t^k) + \varepsilon_t \qquad (C.2)$$

If $\lambda^k > 1$ ($\lambda^k < 1$), the probability of informed trading in market k is higher (lower) than in the consolidated market, as observed imbalances are of greater (lower) magnitude than expected from its actual market share.

Table C.1 detail the estimation results for both Chi-X (Panel A) and the Primary Markets (Panel B). The first two columns report the mean and median coefficients from stock-specific OLS regressions for the entire sample and the different activity terciles, while the latter two columns contain the p-values from t-tests and Wilcoxon rank sum tests. Overall, the evidence indicates excess informed trading on Chi-X and a shortfall of informed traders on the Primary Markets. Except for the tercile with the most active stocks, the mean (median) regression coefficient for the MTF exceeds one, while the one for the Primary Markets is less than one.

We then use the product $(\hat{\lambda}_i^C - 1)\sigma_i$ as another measure of ΔAS_i in regression (12), where $\hat{\lambda}_i^C$ is the regression coefficient from equation (C.2) using the Chi-X imbalance as independent variable, and σ_i denotes stock i's annualized return volatility. The results can be found in Table C.2, where we also show the coefficients for the alternative specification using Chi-X's market share in terms of trades. The coefficients are negative and statistically significant, which is in line with the results obtained using the other measures of the adverse selection risk differential. Nevertheless, the effect's magnitude in terms of economic significance is considerably smaller than for the other variables employed in section 6. For example, a one standard deviation increase in $(\hat{\lambda}_i - 1)\sigma_i$ (~15.44) is associated with a decrease of 1.96% in Chi-X's presence at the best quote, which is less than half of the effect for ΔAS_i^{SD}.

Table C.1: Imbalance Regressions

This table contains summary statistics on the order imbalance regression in equation (C.2) for estimating differences in the probability of informed trading between Chi-X, the Primary Markets, and the consolidated market. Results are based on our sample of 67 French and German stocks, aggregated into terciles based on trading activity. The first two columns present the mean and median regression coefficients minus one, while the last two columns contain p-values from t-tests and non-parametric Wilcoxon signed-rank tests.

Panel A: Imbalance Regressions for Chi-X				
	λ-1		p-value (Ho: λ=1)	
	Mean	Median	T-test	Wilcoxon
High Volume	0.095	-0.003	0.419	0.518
Medium Volume	0.322	0.301	<0.001	<0.001
Low Volume	0.275	0.279	0.034	0.012
All	0.232	0.219	<0.001	<0.001
Panel B: Imbalance Regressions for Primary Markets				
	λ-1		p-value (Ho: λ=1)	
	Mean	Median	T-test	Wilcoxon
High Volume	0.001	0.003	0.952	0.863
Medium Volume	-0.034	-0.032	0.002	0.002
Low Volume	-0.031	-0.030	0.026	0.018
All	-0.021	-0.027	0.012	0.008

Table C.2: Cross-sectional regressions

This table contains estimates for the linear cross-sectional regression following equation (13), where column headings denote the dependent variable. All variables are described in Section 5. Robust standard errors are given in parentheses. Statistical significance at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	% Chi-X at inside quote	Chi-X Market Share
(λ-1)σ	- 0.127*	- 0.061**
	(0.072)	(0.029)
% Smart Routers	0.095	0.330***
	(0.196)	(0.055)
ln(Volume)	5.780***	1.971***
	(1.804)	(0.588)
Synch	2.009	0.965*
	(1.569)	(0.530)
Δtick (bps)	3.066***	0.838***
	(0.706)	(0.210)
Euronext dummy	-1.984	- 3.589***
	(2.538)	(0.833)
Constant	- 64.334*	- 39.253***
	(37.762)	(12.077)
N	67	67
Adj. R^2	0.505	0.575