Adverse selection, market access, and inter-market competition ☆

CrossMark

Peter Hoffmann

European Central Bank, Financial Research Division, Sonnemannstr. 22, 60314 Frankfurt am Main, Germany

ABSTRACT

This paper investigates the role of informed trading in a fragmented financial market under the absence of inter-market price priority. Due to frictions in traders' market access, liquidity providers on alternative trading platforms can be exposed to an increased adverse selection risk. As a consequence, the main market will dominate (display better quotes) frequently albeit charging considerably higher transaction fees. The empirical analysis of a dataset of trading in French and German stocks suggests that trades on Chi-X Europe, a 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 Europe's quotes and this *excess* adverse selection risk faced by liquidity providers in the cross-section.

© 2015 Elsevier B.V. All rights reserved.

1. Introduction

The introduction of the Markets in Financial Instruments Directive (MiFID) in late 2007 spawned competition among stock exchanges across Europe by allowing so-called multilateral trading facilities (henceforth MTFs) to compete directly with the national stock exchanges (Primary Markets) for customer order flow. Ultimately, MiFID aimed 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 are responsible 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 to 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 can benefit the Primary Markets and therefore limit inter-market competition. To this end, we study how market access frictions give rise to differences in adverse selection risks across trading venues in the absence of inter-market price priority. Inspired by the 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 sample of trades and quotes in German and French stocks from April–May 2008 confirms the existence of imperfections in traders' routing abilities, as only about every second trade originates from agents with perfect access to Chi-X Europe (henceforth Chi-X), the only existing MTF at that time. Moreover, trades executed on this alternative 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.

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., 2008; 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 frictions in traders' routing abilities, we consider a model with a risky asset and asymmetric information. We therefore contribute to the literature by studying the role of market access frictions (together with the absence of a trade-through rule) for inter-market competition through differences in informed trading. A similar angle is analyzed by van Kervel (2015), who shows how inter-market competition can lead to an "overprovision" of liquidity.

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., 1996; 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., 2008) 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

This section presents a simple model of informed trading with two trading venues, based on Glosten and Milgrom (1985). We focus on deriving conditions for market co-existence in equilibrium.

2.1. Model setup

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 $N^P \geqslant 2$ and $N^C \geqslant 2$ identical, risk neutral market makers, respectively, who post bid and ask quotes for a single unit of the risky asset. There is a continuum of traders (of unit mass), who arrive sequentially at time points $t = 1, \ldots, T$. They can buy or sell at most one unit of the asset and then exit the market forever. A proportion $\mu \in (0, 1)$ of the trader population is perfectly informed about the liquidation value V, while the remaining traders are uninformed.

We make two crucial assumptions concerning the way in which trading platforms differ. First, in line with the observation that entering MTFs offered trading at considerably lower fees, we assume that market P charges a cost $c > 0$ per trade to market makers, while the cost charged by market C is normalized to zero.[2] Naturally, c is assumed to be very small in comparison to the asset's fundamental uncertainty, $(\overline{V} - \underline{V})$. Second, following Foucault and Menkveld (2008), we assume that access to market C is imperfect because it requires the use of smart order routing technology. Further supporting evidence for this assumption is presented in Section 3.2. Let $\theta^I < 1$ and $\theta^U < 1$ denote the respective fractions of informed and uninformed traders that can trade in both markets. We call these agents smart routers. The remaining agents are assumed to be only able to trade in market P, and we call them captive traders. Fig. 1 graphically depicts the structure of the trader population for the case $\theta^I > \theta^U$.

The overall proportion of smart routers is given by $\theta = \mu\theta^I + (1 - \mu)\theta^U$. The proportion of informed traders among smart routers and captive traders, respectively, are defined as

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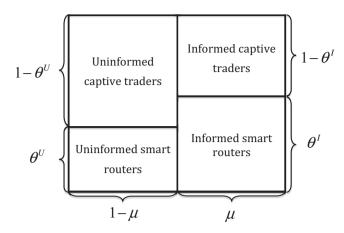

Fig. 1. Trader Population. This figure depicts the trader population for the case $\theta^I > \theta^U$.

It is easy to see that $\theta^I > \theta^U$ ($\theta^I < \theta^U$) implies $\mu^{SR} > \mu > \mu^{CT}$ ($\mu^{SR} < \mu < \mu^{CT}$). Traders always choose to trade in the market that offers the better price given their trading interest and market access. As usual, we assume that uninformed traders buy or sell with equal probability. In contrast, informed traders buy if $V = \overline{V}$ and the best available ask is less or equal to $\overline{V}$, and sell if $V = \underline{V}$ and the best available bid is greater or equal to $\underline{V}$. Otherwise, they do not trade.

We make one additional technical assumption in order to deal with situations where both venues display identical quotes. Due to the absence of a minimum tick size, even the introduction of fees for market orders cannot prevent such ties because agents would base their routing decisions on net prices, as in Colliard and Foucault (2012). As the introduction of a tick size complicates the model 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. In Section 3.2, we provide strong empirical support for this assumption.

If several market makers within the same market post the same price, we assume that the incoming order hits one of them randomly with equal probability. 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, which implies that they hold identical beliefs about the likelihood that $V = \overline{V}$ at all times.[3] Let δ_{t-1} denote this common belief prior to the arrival of the t-th trader.

2.2. Equilibrium and market co-existence

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 $i = 1, \ldots, N^P$ and $j = 1, \ldots, N^C$. Moreover, define the best bid in market k as $b_t^k = \max\{b_t^{1,k}, \ldots, b_t^{N^k,k}\}$ for $k \in \{P, C\}$.

Given that captive traders can only trade in market P, the probability of a sell occurring in market P is always strictly positive. On the other hand, trade will 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.

Definition (*Market co-existence*). *Markets co-exist iff $b_t^C \geqslant b_t^P$.*

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 at time t if and only if*

$$c \geqslant \Delta AS_t, \tag{1}$$

where

$$\Delta AS_t = (\overline{V} - \underline{V})\,(\mu^{SR} - \mu)\Psi_B(\delta_{t-1})$$

and

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

Proof. See Appendix A. □

The intuition behind Eq. (1) is straightforward. It contrasts the cross-market differential of the two components of trading costs, exchange fees and adverse selection costs. While the left-hand side represents market C's cost advantage, c, the right-hand side measures the competitive (dis-)advantage related to informed trading, ΔAS_t. The latter crucially depends on whether smart routers are more or less informed than the average trader.

If $\mu^{SR} > \mu$ (or equivalently $\theta^I > \theta^U$), quoting in market C is cheaper, but riskier ($\Delta AS_t > 0$). While market makers save the cost c, their quotes face a higher proportion of informed traders. Accordingly, they are not able to match the quotes posted in market P if the excess adverse selection risk is too large. However, notice that the risk of informed trading is not constant, but varies over time as market makers update their beliefs based on the order flow. This is captured by the function $\Psi_B(\delta_{t-1})$, which ensures that ΔAS_t approaches zero as the number of trading rounds grows large. So while excess adverse selection may prevent market co-existence in earlier trading rounds, Condition (1) is necessarily satisfied in the limit.

If conversely $\mu^{SR} \leqslant \mu$ (or equivalently $\theta^I \leqslant \theta^U$), Condition (1) is always satisfied. Market C has an advantage not only in terms of fees, but also in terms of adverse selection costs, $\Delta AS_t < 0$. Accordingly, markets always co-exist.

Proposition 1 has an empirical implication for Chi-X's quote competitiveness in the cross-section. To see this, consider two assets, A and B, and assume that the stock-specific adverse selection differential across markets is larger for asset A for all possible beliefs, i.e., $\Delta AS_A(\delta_{t-1}) > \Delta AS_B(\delta_{t-1})$. It follows that for $c < \max_{\delta_{t-1}} \Delta AS_A(\delta_{t-1})$, there are beliefs for which markets co-exist for asset B, but not for asset A.[4] Intuitively, market P has a comparative advantage for asset A because of a larger cross-market adverse selection risk differential. Accordingly, market C will display more competitive quotes for asset B. This leads us to the following prediction, which will be tested empirically in Section 5.

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

2.3. Comparison to Foucault and Menkveld (2008)

Given that we share the key assumption in Foucault and Menkveld (2008) of imperfect access to market C, it is instructive

---

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

[4] In the converse case, $c > \max_{\delta_{t-1}} \Delta AS_A(\delta_{t-1})$, markets will always co-exist for both assets.

to briefly contrast our model with theirs. In their model, infra-marginal limit orders earn positive expected profits due to the assumption of a minimum tick size. Combined with price-time priority, this friction generates market co-existence: A larger cue of limit orders in one market implies a low execution probability, thus providing incentives to jump the cue by quoting in the other market. In contrast, our model abstracts from the role of a minimum tick size and instead focuses on the role of heterogeneity among smart routers. While market C charges lower fees, its existence can be hampered by excessive adverse selection. More specifically, if the share of informed traders among smart routers is too large relative to the overall trader population, liquidity providers will not be able to post competitive quotes on this platform. That is, market C's success crucially depends on attracting the "right" types of market participants (uninformed traders). In Foucault and Menkveld (2008), there is no asymmetric information and no heterogeneity among smart routers. Accordingly, an increase in the proportion of smart routers always benefits the entrant market because it increases the execution probability of the limit orders posted there.

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 derived in Section 2.2. 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. In late 2011, the trading platform was acquired by Bats Trading, a competing MTF. According to Fidessa[5], Chi-X's market share in the first half of 2015 was slightly above 20% for the major European 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 new market entrants.

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 relatively similar and significantly exceed those on Chi-X, particularly for orders providing liquidity.[6]

Aside from the exchange fees, transactions involve additional costs as trades are cleared and settled via a central counterparty (CCP). As all three markets under consideration are using different clearing houses for this purpose, competition in terms of fees is extended to the post-trade environment. CMCF, Chi-X's clearing house, charges a flat fee of €0.19 per trade, which is considerably cheaper than the €0.23 and €0.30 (plus 0.15 bps) charged by its competitors' CCPs, LCH.Clearnet (Euronext) and Clearstream (Xetra). Thus, the additional consideration of settlement costs amplifies Chi-X's advantage in terms of fees.

Besides charging considerably lower fees, Chi-X distinguishes itself from the Primary Markets in several other aspects. Most prominently, the MTF specifically targets algorithmic and high-frequency traders via an ultra-low system latency, which according to the platform[7] 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. 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.

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 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 (trades are simply matched to the quotes prevailing prior to the transaction). Merging the BBO data from Chi-X and the Primary Markets, we obtain the European Best Bid and Offer (EBBO).[8] We restrict our analysis to the continuous trading phase,

---

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

[6] 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.

[7] "Chi-X celebrates its first anniversary", Chi-X press release, 07.04.2008.

[8] One potential concern is the fact that our data stem from two different sources, such that the time-stamps are not fully synchronized. In order to mitigate potential concern with respect to this issue, we perform some sensitivity checks by lagging the Reuters time stamp (which should record the feeds from the Primary Markets with a small delay) between 0.1 and 0.5 s. We find that our results are insensitive to potentially asynchronous timestamps.

which spans the time between 9:00 and 17:30 CET. Moreover, we remove hidden orders executed on Chi-X, as no such orders are admitted on the Primary Markets.[9]

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.

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.

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 MTF 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.

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.

	Chi-X	Primary	MS Chi-X (%)
Panel A: Avg. daily # of trades (1000 trades)			
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. €)			
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
	Chi-X	Primary	Ratio C/P (%)
Panel C: Average trade size (€1000)			
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 computed using 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)

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 relative 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

$$AS_t = q_t \frac{m_{t+\Delta t} - m_t}{m_t} \qquad (3)$$

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 $t + \Delta t$ 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 compute 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 favor 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 before fees.

Nevertheless, a look at the spread decomposition[10] (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.

Net of transaction and clearing fees, market makers' revenues can be expected to be relatively similar across markets (notice that Chi-X grants a rebate of 0.2 bps for limit orders, while the Primary Markets charge a positive fee). Moreover, the fact that revenues from liquidity provision are very close to zero indicates a very competitive market.

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 Eqs. (2)–(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.

	Chi-X	Primary	Difference
Panel A: Effective spread			
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			
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			
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)

Overall, the effective spread decomposition clearly suggests that liquidity providers on Chi-X face a higher adverse selection risk. This is consistent with the MTF's focus on attracting latency-sensitive clients such as high-frequency traders, whose orders have been shown to have larger permanent price impacts than slower market participants.[11] The 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 (these negative differences are not statistically different from zero).[12] 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 compute the effective spread decomposition for both types of transactions.

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,

---

[10] We set $\Delta t = 5$ min. Setting the interval to 15 or 30 min delivers qualitatively similar results.

[11] See, e.g., Brogaard et al. (2014), or Brogaard et al. (2015).

[12] For the sake of parsimony, we do not report the results for individual stocks (available upon request).

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 Eqs. (2)–(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.

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

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

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

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

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

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,[13] and truncate the VAR after 10 lags.[14] 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

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

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 $PI^C = \sum_{i=0}^{\infty} C_i$.

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

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

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

---

[13] Estimating the model with data aggregated to 5-s 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.

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

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

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, Eqs. (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)

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

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

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.

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 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.[16] 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

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

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.

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[17], which we define as the average[18] 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 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).[19] 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 Menveld, 2012). While trading volume is simply a variable outside our model, the results in Hengelbrock and Theissen (2009) suggest that trading in more active stocks has a higher tendency to fragment.

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

---

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

[17] 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.

[18] 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.

[19] 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.

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.

	$\Delta AS(SD)$	$\Delta AS(HB)$	σ
$\Delta AS(SD)$	1.000	0.635***	0.424***
$\Delta AS(HB)$		1.000	0.453***
σ			1.000

Table 10
Cross-sectional regressions. This table contains estimates for the linear cross-sectional regression following Eq. (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)
$\Delta AS(SD)$	−11.748***		
	(2.692)		
$\Delta AS(HB)$		−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 Eq. (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)	(3)
$\Delta AS(SD)$	−2.989***		
	(1.091)		
$\Delta AS(HB)$		−6.997***	
		(1.862)	
σ			−0.137**
			(0.059)
% Smart routers	0.318***	0.273***	0.305***
	(0.059)	(0.056)	(0.061)
ln(volume)	2.491***	2.735***	2.020***
	(0.419)	(0.403)	(0.419)
Synch	1.390**	1.106**	1.726***
	(0.549)	(0.500)	(0.575)
Δtick (bps)	1.094***	1.235***	0.939***
	(0.271)	(0.217)	(0.244)
Euronext dummy	−3.472***	−2.232***	−3.542***
	(0.748)	(0.827)	(0.757)
Constant	−47.826***	−50.598***	−34.990***
	(8.668)	(7.702)	(9.344)
N	67	67	67
Adj. R^2	0.588	0.643	0.572

large, similar to the results using Chi-X's presence at the inside quote.

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 European regulatory framework set forth under MiFID, we analyze how market access frictions give rise to differences in adverse selection risks across markets in the absence of inter-market price priority. We argue that liquidity providers on alternative trading platforms are 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 (an MTF launched under MiFID) 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.

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.

Appendix A. Proof of Proposition 1

As trader populations differ across markets, so does the function that maps market makers (henceforth MMs) prior into their poste-

by one standard deviation ($\sim$2.2 bps) leads Chi-X's presence at the best quote to increase by 7–11%, depending on the specification. Different from Foucault and Menkveld (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 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 Eq. (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 to 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

rior 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,

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

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

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

This implies the following conditional expectations of the liquidation value.

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

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

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

Clearly, $\mu^{SR} > \mu > \mu^{CT}(\mu^{SR} < \mu < \mu^{CT})$ implies $B(\mu^{CT}, \delta_{t-1}) \geqslant B(\mu, \delta_{t-1}) \geqslant B(\mu^{SR}, \delta_{t-1})$ $(B(\mu^{CT}, \delta_{t-1}) \leqslant B(\mu, \delta_{t-1}) \leqslant B(\mu^{SR}, \delta_{t-1}))$, 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 $i = 1, \ldots, N^P$ and $b_t^{j,C*} < b_t^{P*}$ for $j = 1, \ldots, N^C$ constitutes a symmetric Nash equilibrium. All trade occurs in market P, and MMs obtain zero expected profits in both markets. It is straightforward to verify that any unilateral deviation cannot be profitable in either market.

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, we must have $b_t^{C*} \leqslant B(\mu^{SR}, \delta)$. But then, MMs in market P have incentives to unilaterally increase their bids to increase expected profits. Hence, this cannot be an equilibrium. Now consider the situation where $b_t^{P*} = b_t^{C*}$. It is easy to see that this requires $b_t^{P*} = b_t^{C*} = B(\mu^{SR}, \delta)$. Then, MMs in market P earn expected profits of $\Pi = (1-\theta)\,(B(\mu^{CT}, \delta) - B(\mu^{SR}, \delta) - c)/N^P > 0$. If MM i would marginally increase her bid to $b_t^{i,P} = B(\mu^{SR}, \delta) + \varepsilon < B(\mu, \delta) - c$, she would earn $B(\mu, \delta) - B(\mu^{SR}, \delta) - c - \varepsilon$, which is always greater than Π for $N^P \to \infty$.

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

For this case, $b_t^{j,C*} = b_t^{i,P*} = B(\mu^{SR}, \delta)$ for $i = 1, \ldots, N^P$ and $j = 1, \ldots, N^C$ is a symmetric Nash equilibrium. Given our assumption regarding inter-market ties, smart routers trade in market C and captive traders trade in market P. MMs in market C earn zero expected profits and MMs in market P earn $\Pi = (1-\theta)[B(\mu^{CT}, \delta) -$

$c - B(\mu^{SR}, \delta)]/N^P \geqslant 0$. It is easy to check that unilateral deviations are not profitable. To see that we must have $b_t^{C*} = b_t^{P*}$, first assume that $b_t^{C*} > b_t^{P*}$. In this case, $b_t^{C*} = B(\mu^{SR}, \delta)$, which allows MMs in market P to increase profits by increasing their bid (they face μ^{CT} informed traders). Conversely, if $b_t^{P*} > b_t^{C*}$, we must have $b_t^{P*} = B(\mu, \delta) - c$. But then, MMs in market C face a proportion μ^{SR} of informed traders, and $B(\mu^{SR}, \delta) \geqslant B(\mu, \delta) - c$ implies that they can increase their expected profits by increasing their bids. 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 $i = 1, \ldots, N^P$ and $j = 1, \ldots, N^C$ constitutes a symmetric Nash equilibrium. Smart routers trade in market C, captive traders in market P, and all MMs obtain zero expected profits. Unilateral deviations cannot be profitable. To see that we must have $b_t^{C*} > b_t^{P*}$ in equilibrium, it suffices to note that $b_t^{C*} \leqslant b_t^{P*}$ requires $b_t^{P*} \leqslant B(\mu^{CT}, \delta) - c$. But then, MMs in market C can make profits by increasing their bids because $B(\mu^{SR}, \delta) > B(\mu^{CT}, \delta) - c$. Hence this cannot be an equilibrium.

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

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

In this case, we trivially always have $B(\mu^{SR}, \delta) > B(\mu^{CT}, \delta) - c$. Hence the equilibrium is the same as in case A3. Markets co-exist and Condition (1) is satisfied. $\quad\square$

References

Barclay, M.J., Hendershott, T., McCormick, D.T., 2003. Competition among trading venues: information and trading on electronic communication networks. Journal of Finance 58, 2637–2666.

Battalio, R., Greene, J., Hatch, B., Jennings, R., 1997. Does the limit order routing decision matter? Review of Financial Studies 15, 159–194.

Bessembinder, H., 2003. Quote-based competition and trade execution costs in NYSE-listed stocks. Journal of Financial Economics 70, 385–422.

Bessembinder, H., Kaufman, H., 1997. A cross-exchange comparison of execution costs and information flow for NYSE-listed stocks. Journal of Financial Economics 46, 293–319.

Biais, B., Bisière, C., Spatt, C., 2010. Imperfect competition in financial markets: an empirical study of Island and Nasdaq. Management Science 56, 2237–2250.

Boehmer, B., Boehmer, E., 2004. Trading your neighbor's ETFs: competition and fragmentation. Journal of Banking & Finance 27, 1667–1703.

Brogaard, J., Hendershott, T., Riordan, R., 2014. High-frequency trading and price discovery. Review of Financial Studies.

Brogaard, J., Hagströmer, B., Norden, L., Riordan, R., 2015. Trading fast and slow: co-location and market quality. Review of Financial Studies (forthcoming).

Chowdry, B., Nanda, V., 1991. Multimarket trading and market liquidity. Review of Financial Studies 4, 485–511.

Colliard, J.-E., Foucault, T., 2012. Trading fees and efficiency in limit order markets. Review of Financial Studies 25, 3389–3421.

Easley, D., Kiefer, N.M., O'Hara, M., Paperman, J.B., 1996. Liquidity, information, and infrequently traded stocks. Journal of Finance 51, 1405–1436.

Foucault, T., Menkveld, A., 2008. Competition for order flow and smart order routing systems. Journal of Finance 63, 119–158.

Glosten, L., Milgrom, P., 1985. Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. Journal of Financial Economics 14, 71–100.

Goldstein, M.A., Shkilko, A.V., Van Ness, B.F., Van Ness, R.A., 2008. Competition in the market for Nasdaq securities. Journal of Financial Markets 113–143.

Gomber, P., Gsell, M., 2010. Catching up with technology – The impact of regulatory changes on ECNs/MTFs and the trading venue landscape in Europe. Competition and Regulation in Network Industries.

Grammig, J., Schiereck, D., Theissen, E., 2001. Knowing me, knowing you: trader anonymity and informed trading in parallel markets. Journal of Financial Markets 4, 385–412.

Harris, L.E., 1994. Minimum price variations, discrete bid-ask spreads, and quotation sizes. Review of Financial Studies 7, 149–178.

Hasbrouck, J., 1991. Measuring the information content of stock trades. Journal of Finance 46, 179–207.

Hendershott, T., Riordan, R., 2009. Algorithmic Trading and Information. Working Paper.

Hengelbrock, J., Theissen, E. 2009. Fourteen at One Blow: The Market Entry of Turquoise. Working Paper.

Jovanovic, B., Menveld, A. 2012. Middlemen in Securities Markets. Working Paper.

Lee, C.M.C., Ready, M.J., 1991. Inferring Trade Direction from Intraday Data. Journal of Finance 46, 733–746.

Madhavan, A., 1995. Consolidation, fragmentation, and the disclosure of trading information. Review of Financial Studies 8, 579–603.

Pagano, M., 1989. Trading volume and asset liquidity. Quarterly Journal of Economics 104, 255–274.

Parlour, C.A., Rajan, U., 2003. Payment for order flow. Journal of Financial Economics 68, 379–411.

Petrella, G. 2009. MiFID, Reg NMS and Competition Across Trading Venues in Europe and United States. Working Paper.

Shkilko, A.V., Van Ness, B.F., Van Ness, R.A., 2008. Locked and crossed markets on NASDAQ and the NYSE. Journal of Financial Markets 11, 308–337.

Teoh, S.H., Yang, Y.G., Zhang, Y. 2008. R-Square and Market Efficiency. Working Paper.

van Kervel, V., 2015. Competition for order flow with fast and slow traders. Review of Financial Studies 28, 2094–2127.