Can fast and slow liquidity providers co-exist in modern equity markets?☆

Sean Foley,[a] Arseny Gorbenko,[b,*] and Thomas Ruf [c]

[a] *University of Sydney*
[b] *University of New South Wales*
[c] *Indiana University*

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Abstract

Yes. We study competition between slow and fast market makers (MMs) in Australian equities. We find that the increased competition on speed from high-frequency market makers (HFT MMs) reduces but does not eliminate participation of slower MMs in liquidity provision. Slower MMs start to earn less dollar profits, but round-trip profitability of their trades remains the same. These results indicate that HFT MMs do not expose slower MMs to increased adverse selection. However, these findings only hold when the bid-ask spread is constrained by the minimum tick size. Tick-constrained spreads appear to help slower MMs in retaining profitability of their market-making business when competition on speed increases.

Keywords: market maker, liquidity provision, speed competition, high frequency trading, HFT

JEL classification: G10, G14, G24

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* Corresponding author. School of Banking & Finance, UNSW Business School, Sydney NSW 2052 Australia.
E-mail address: a.gorbenko@unsw.edu.au (A. Gorbenko).

1. Introduction

Liquidity provision in modern stock markets has shifted from designated market makers with firm commitments to supply liquidity to voluntary market makers (MMs). Electronic limit order books (LOBs) allow anyone to provide liquidity by posting a limit order, which simplifies entry into the market-making (MMing) business and increases competition among MMs. Given how crucial liquidity is for a sound financial market, it is important to understand the forces driving competition among liquidity providers.

Theory indicates that voluntary MMs compete primarily on price and speed (e.g., Glosten, 1994; Biais, Martimort, and Rochet, 2000; Aït-Sahalia and Sağlam, 2017; Li, Wang, and Ye, 2019). However, the minimum tick size often restricts price competition. When the bid-ask spread is restricted by the minimum tick size, traders cannot submit price-improving limit orders. In fact, the bid-ask spread of the median stock in our sample is constrained by one tick 92% of the time, leaving less than 30 minutes during a day for potential price improvements.[1] This situation induces a one-dimensional competition on speed, which is of great importance given the time priority rule in the LOB. Traders with a relative speed advantage such as high-frequency traders (HFTs) often exploit these market conditions and act as voluntary MMs (see, e.g., Menkveld, 2013; Hangströmer and Nordén, 2013; Carrion, 2013; Malinova and Park, 2015; Malinova and Park, 2016). This paper investigates how high-frequency market makers (HFT MMs) change competition in liquidity provision.

Competitive advantage in speed should shift liquidity provision from slower to faster MMs who are more effective at acquiring the front position in the limit order queue. Yet, the way it happens may differently impact on health of liquidity provision environment. On the one hand, faster traders can impose higher adverse selection risks on slower traders (Hoffman, 2014; Biais, Foucault, and Moinas, 2015; Budish, Cramton, and Shim, 2015). HFT MMs are quick at canceling their stale quotes, thereby avoiding the risk of being picked off by informed traders. But this risk then transfers to slower MMs staying behind in the limit order queue. On the other hand, canceling quotes gives time priority to the rivals who are behind in the queue. If an HFT MM decides to cancel an order while the bid-ask spread is constrained by the minimum tick increment, she could

[1] Our sample is comprised of the largest 200 Australian stocks. An average NYSE stock has a bid-ask spread constrained by one tick for 50%–60% of the time (O'Hara, Saar, and Zhong, 2019), while an average NASDAQ stock is tick-constrained for 40% of the time (Yao and Ye, 2018).

not easily restore her front queue position as she cannot undercut other limit orders by price. Moreover, the limit order queue at the best bid and offer (BBO) often becomes long in a tick-constrained environment (Yao and Ye, 2018), so that the new limit orders can only be put at the end of the queue. In this case HFT MMs may choose to restrict their order cancelation activities, so that they can reserve their front queue position at the expense of bearing additional adverse selection risks. As a result, slower MMs staying behind in the queue would not incur increased adverse selection costs when HFT MMs operate in the market.

We aim to find the dominating channel when faster traders take over the MMing function. We do not observe quoting activities of slow and fast MMs, but we can distinguish between the channels by analyzing profitability of MMs' liquidity-providing trades. In both of the above scenarios HFT MMs diminish slower MMs' participation in liquidity provision, thus reducing their *dollar profits* from the MMing business. However, increased adverse selection in the first scenario also leads to a drop in *percentage profitability*, i.e., an average MMing round-trip trade would earn lower percentage return. The second scenario does not imply additional adverse selection costs and therefore is not associated with decreased round-trip trade profitability. So, the first scenario may drive slower MMs out from liquidity provision as it could become completely unprofitable. In the second scenario slower traders can maintain their MMing business as it remains profitable, although the amount of capital devoted to this strategy would likely decline. Aït-Sahalia and Sağlam (2017) predict that competition from slower MMs preserved in the second scenario would not allow HFT MMs to price-discriminate other traders, leading to a healthier liquidity provision environment.

We employ a unique broker-level dataset on the Australian stock market to identify MMs, measure their realized profits from liquidity provision, and how these profits change with the increasing role of HFT MMs. First, we detect traders whose MMing strategies constitute a significant proportion of their activities, according to the level of non-directional passive trading. Then, we take stock-days on which they are involved in MMing and calculate total profits ($AUD) and average round-trip trade profitability (%) on these days. We investigate how profits and trade profitability of slow and fast MMs change in response to increased speed competition. Specifically, we focus on the exogeneous shock to speed competition—introduction of the new technology that improved connection speed to the Australian Securities Exchange (ASX) on April 2, 2012—that favored HFT MMs.

We find that the introduction of the new speed technology significantly reduces profits, but not round-trip trade profitability, of slower MMs. On average, a slower MM earns around $AUD 800 less in a stock on a day when she employs her MMing strategy. It translates into a substantial $AUD 32,000 of forgone profits per day. Nevertheless, slower MMs continue to earn positive profits from liquidity provision, and profitability of their MMing trades does not deteriorate. These results are consistent with HFT MMs leaving their orders longer at the BBO when the spread is tick-constrained as in O'Hara et al. (2019). So, transit of MMing function towards HFTs let the slower MMs survive and still earn some money from liquidity provision, at least when price competition is limited by the minimum tick size.

At the same time, profits of an average HFT MM increase by around $AUD 460 per stock-day following the introduction of the new speed technology, which translates into $AUD 32,500 increase in daily profits. Yet, trade profitability of HFT MMs remains at the same level.

To shed more light on the adverse selection channel implied by the queuing mechanism we split trades of MMs to the ones executed in a tick-constrained vs. tick-*un*constrained environment. We investigate how introduction of the new speed technology affect realized spreads and price impacts right after execution of passive trades. We find that passive trades of slower MMs exhibit similar realized spreads and price impacts when the bid-ask spread is constrained by the minimum tick size. It means that slower MMs do not incur additional adverse selection costs in a tick-constrained environment when they face increased speed competition from HFT MMs. Yet, passive trades of slower MMs exhibit decreased realized spreads and increased price impacts in a tick-*un*constrained environment, which indicates that they get adversely selected. Hence, tick-constrained environment seems to be more plausible for slower MMs when HFT MMs start to compete on speed more fiercely.

In additional analysis we look at the effect of fragmentation, which increases during our sample period, on profits of slower and faster MMs. We find that the entry of the new exchange (Chi-X) on October 31, 2011, does not significantly affect slower MMs. Conversely, HFT MMs enjoy higher profits and profitability from stocks traded more heavily on the entrant venue. It is consistent with HFT MMs jumping ahead of queue to the market with more favorable quotes when trade-throughs are allowed (Foucault and Menkveld, 2008).[2] So, we do not find that increased fragmentation leads to decreased profits from liquidity provision via intensified price competition

[2] Unlike in North America and similar to Europe, Australian market does not prohibit trade-throughs.

among MMs as in European markets (Foucault and Menkveld, 2008; Degryse, de Jong, and van Kervel, 2015). It likely happens due to a modest market share of Chi-X during our sample period, which may disincentivize market participants to invest into the smart order router (SOR) technology to access the new market in line with the idea in Foucault and Menkveld (2008).

Our research contributes to understanding how trading speed affects liquidity provision. A number of papers argue that the speed arms race may impair liquidity provision by increasing adverse selection risks (e.g., Hoffman, 2014; Biais et al., 2015; Budish et al., 2015; Foucault, Kozhan, and Tham, 2017; Menkveld and Zoican, 2017; Shkilko and Sokolov, 2019). Yet, many studies conclude that fast trading improves liquidity (e.g., Hendershott, Jones, and Menkveld, 2011; Riordan and Storkenmaier, 2012; Hasbrouck and Saar, 2013; Brogaard, Hangströmer, Nordén, and Riordan, 2015). Our results may reconcile the above findings. When a tick-constrained spread prevents price undercutting, a limit order queue at the BBO becomes long, so that fast MMs prefer to bear additional adverse selection risk to retain their time priority in the queue. This restraining queuing mechanism precludes adverse selection risk to be transferred to slower MMs, letting them survive and provide liquidity, which makes the limit order queue longer, discouraging HFT MMs from cancelling their quotes, and so on. Although we do not observe quoting strategies of MMs, non-decreasing profitability levels that we document for slower MMs support this mechanism. Therefore, better liquidity levels attributable to increased HFT activity might be driven by tick-constrained stocks, while other stocks experience greater adverse selection and deterioration in liquidity consistent with the findings in O'Hara et al. (2019).

Our results complement the recent debate on a potential tick size increase in the United States. The 2012 Jumpstart Our Business Startups Act proposes to raise the tick size for small capitalization stocks to incentivize liquidity providers. Our findings suggest that it would most positively affect those stocks whose bid-ask spreads shifts from the tick-unconstrained to tick-constrained environment, as it would enforce the queuing mechanism described above. Stocks that are tick-constrained might not benefit as they already have this mechanism in place.[3] Yao and Ye (2018) and O'Hara et al. (2019) find that higher HFT activity in stocks with large relative tick size,

[3] Rindi and Werner (2019) and Griffith and Roseman (2019) among others, investigate how the SEC experiment that increased the tick size from \$0.01 to \$0.05 for a random sample of small capitalization stocks affected liquidity. They report deteriorating liquidity measures for the treated stocks that *are* tick-constrained after the increase. The restraining queuing mechanism that we describe here implies that the subset of these stocks that were tick-unconstrained but *have become* tick-constrained might be better off.

resulting from HFTs' usage of their relative speed advantage, leads to greater depth at the BBO. Given that these stocks are likely to be tick-constrained, the queuing mechanism, and competition from slower MMs in particular, would also contribute to the depth of these stocks.

Our paper fits into to the literature on competition among liquidity providers. The earlier studies show that price competition can drive profits from liquidity provision to zero (Glosten, 1994), albeit the finite number of MMs ensures positive gains from MMing (Biais et al., 2000; Biais, Bisière, and Spatt, 2010). When price and speed competition are combined, fast MMs may completely replace slow MMs by imposing the latter to increased adverse selection (e.g., Hoffman, 2014; Han, Khapko, and Kyle, 2014; Bongaerts and van Achter, 2016; Bernales, 2019). However, tick-constrained spreads, persistent in many stocks nowadays, restrict such competition. In this sense, our results are most consistent with the theory of Aït-Sahalia and Sağlam (2017), predicting co-existence of fast and slow MMs.

Many papers view HFTs as the main endogenous liquidity providers (e.g., Malinova and Park, 2015; Malinova and Park, 2016; Anand and Venkataraman, 2016; Brogaard, Carrion, Moyaert, Riordan, Shkilko, and Sokolov, 2018). We find that investment banks, which primarily operate on behalf of buy-side institutions, significantly contribute to the supply of liquidity in the market. More than 50% of passive trading volume in Australia comes from investment banks that behave as MMs according to their level of non-directional passive trading. Yet, they do not earn profits from liquidity provision: approximately half of their trading days that look like MMing bring losses. It supports the view on the structure of liquidity provision modelled by Li et al. (2019) who show that execution algorithms of buy-side institutions can supply liquidity to the market with an intention to minimize transaction costs rather than to make markets and earn the spread.

2. Theory and hypotheses

MMs can employ different trading strategies to earn the spread, but they cannot differentiate their end "product"—liquidity in the form of a limit order—from other liquidity providers. Unlike mutual funds designing unique strategies to attract certain clientele (Kostovetsky and Warner, 2019), "customers" of MMs do not know who is supplying liquidity to them. The price-time priority rule in lit equity markets only ensures that a liquidity taker would consume a limit order with the best price and earliest submission time. As a result, voluntary MMs compete on price and speed to become the first in the limit order queue.[4]

Being first in the limit order queue has its pros and cons akin being a specialist MM in the classical market microstructure models (e.g., Glosten and Milgrom, 1985; Kyle, 1985). It enables a liquidity provider to earn the bid-ask spread from uninformed market orders but exposes her to the risk of being picked off by informed traders ("pick-off" risk) as in Foucault (1999).

Speed advantage can put the front limit order queue position to its best use. Hoffman (2014), Han et al. (2014), Bongaerts and van Achter (2016), Aït-Sahalia and Sağlam (2017), and Bernales (2019) among others, demonstrate that a fast MM could cancel her stale order before an incoming information triggers a trade, thus incurring lower adverse selection costs. Consequently, faster MMs can leave slower MMs behind in the limit order queue by posting more competitive quotes, without increasing their pick-off risk. In addition, speed advantage directly helps in acquiring time priority in the queue (Li et al., 2019). Hence is our first testable hypothesis.

Hypothesis 1: Increased speed competition from faster MMs leads to decreased profits ($AUD) of slower MMs.

Hoffman (2014), Han et al. (2014), Bongaerts and van Achter (2016), and Bernales (2019) further predict that fast MMs' ability to cancel their stale quotes would expose the orders behind, which come from slower MMs, to increased pick-off risk. As a consequence, slower liquidity providers would either bear additional adverse selection costs or post less competitive quotes. This could drive slower MMs out of the market. Alternatively, Aït-Sahalia and Sağlam (2017) predict that restricted price competition may force a fast MM to bear most of the adverse selection risk in the market. A long queue at the BBO may restrain a fast MM from frequent quote removal to secure her time priority in the limit order book. In this case slower liquidity providers would not bear additional adverse selection costs, and therefore would not need to post less competitive quotes. More adverse selection costs mean less round-trip trade profitability from MMing in

[4] I use the terms "market makers" (MMs) and "liquidity providers/suppliers" interchangeably throughout the paper. Strictly speaking, they are not the same. MMs are a subset of liquidity suppliers that post bid and ask limit orders to earn the spread. Liquidity suppliers in general can post limit orders for other purposes, e.g., to minimize transaction costs (Li et al., 2019). This paper is mostly about MMs.

general as well as more nominal adverse selection costs borne by passive trades right after they are executed, and vice versa.[5] These two scenarios lead to the following alternative hypotheses.

Hypothesis 2a: Increased speed competition from faster MMs leads to decreased average round-trip trade profitability (%) of slower MMs.
Hypothesis 2b: Increased speed competition from faster MMs does not affect average round-trip trade profitability (%) of slower MMs.

Hypothesis 3a: Increased speed competition from faster MMs leads to increased nominal adverse selection costs borne by passive trades of slower MMs.
Hypothesis 3b: Increased speed competition from faster MMs does not affect nominal adverse selection costs borne by passive trades of slower MMs.

Hypothesis 4a: Increased speed competition from faster MMs leads to decreased proportion of passive trades executed by slower MMs when the bid-ask spread is tick-constrained.
Hypothesis 4b: Increased speed competition from faster MMs does not decrease proportion of passive trades executed by slower MMs when the bid-ask spread is tick-constrained.

In theory, hypotheses 2–3 could be reformulated for faster MMs. However, the empirical testing of this hypotheses is contaminated by the incentives of faster MMs to realize their speed advantage. Specifically, increased opportunities for realizing comparative speed advantage that we exploit in this paper (see Section 3.3 for details) incentivize HFT MMs to enter the market, thus intensifying competition among faster MMs. It biases towards finding non-significant results as the larger number of HFT MMs would share the benefits (costs) of decreased (increased) adverse selection risks between each other. Therefore, we focus on slower MMs as outlined in hypotheses 2–3.

The proliferation of alternative trading venues, characterizing the current state of equity markets (Foucault and Menkveld, 2008; O’Hara and Ye, 2011; Menkveld, 2013; Degryse et al.,

[5] We estimate nominal adverse selection costs borne by MMs by 30-second realized spreads and price impacts. See details in Section 5.2.

2015; He, Jarnecic, and Liu, 2015), may differentially affect fast and slow traders. Specifically, Foucault and Menkveld (2008) predict that SOR systems, which are common for HFTs, can jump ahead of the limit order queue in one market by quoting in another market. This strategy may bring additional profits as well as better trade profitability to a fast MM if trade-throughs are allowed.[6] At the same time, slower MMs without access to the SOR technology would not be able to benefit from this queue-jumping strategy. This leads to the next hypotheses.

Hypothesis 5: Increased fragmentation leads to increased profits ($AUD) and average round-trip trade profitability (%) of faster MMs.

Hypothesis 6: Increased fragmentation does not affect profits ($AUD) and average round-trip trade profitability (%) of slower MMs.

3. Empirical approach

Our empirical approach involves: (i) identifying MMs, (ii) estimating their profits from liquidity provision, and (iii) evaluating how these profits change with exogenous variation in competition among faster and slower MMs.

3.1. Identification of market makers

Australian equity markets have no designated MMs unlike other markets (Menkveld and Wang, 2013; Anand and Venkataraman, 2016; Clark-Joseph, Ye, and Zi, 2017), i.e., all liquidity is provided by voluntary MMs. To identify these MMs we use a two-step procedure. We start by identifying brokers likely to be involved in proprietary MMing according to the level of their non-directional passive trading. We filter off brokers that do not make markets on a regular basis, concentrating on those who purposefully develop and use MMing strategies. Then, we perform a sanity check of potential MMs by analyzing their profits from liquidity provision and browsing

[6] The Australian market allows trading at prices worse than the consolidated BBO quotes. Therefore, a worse quote of a MM in venue A can be executed ahead of a better quote in venue B if a market order arrives to venue A (by a "worse" quote I mean a lower bid or higher ask quotes compared to the ones observed in another market). Hence, posting quotes on many venues can not only increase execution probability, which brings more dollar profits, but also raise round-trip trade profitability.

public information on their MMing activities. As a result of this procedure we obtain the set of MMs whose stock-day observations are categorized as MMing or non-MMing.

A pure MMing strategy implies earning the spread from non-directional trading via posting bid and ask limit orders. Hence, researchers usually identify MMs by focusing on brokers with small end-of-day buy-sell order imbalance (e.g., Malinova and Park, 2015; Malinova and Park, 2016; Comerton-Forde, Malinova, and Park, 2018), signifying non-directional trading during the day. In addition, some studies require a broker to have a certain proportion of passive trades to qualify as a MM to filter off aggressive arbitrage strategies (e.g., Brogaard and Garriott, 2019). We use both criteria for identifying MMs in our sample.

First, we compute the end-of-day absolute buy-sell order imbalance for all stock-days, in which a broker executes non-zero trading volume during our sample period:

$$Order\ Imbalance_{b,s,d} = \left|\frac{Volume\ Bought_{b,s,d} - Volume\ Sold_{b,s,d}}{Volume\ Bought_{b,s,d} + Volume\ Sold_{b,s,d}}\right|, \tag{1}$$

where *Volume Bought* (*Sold*)$_{b,s,d}$ indicates the number of shares bought (sold) by broker *b* in stock *s* on day *d*. Second, we calculate proportion of passive trades for a broker in each stock-day. Since our data provides actual trade directions, we do not need to rely on algorithms like that of Lee and Ready (1991) to determine buyer- and seller-initiated trades. We classify all stock-day observations for each broker as MMing if (i) the broker's order imbalance does not exceed 30%, and (ii) she is passive in at least 50% of the executed trading volume.

Next, we retain only those brokers whose MMing strategies constitute a significant proportion of their activities. Thus, we classify a broker as a potential MM if the median proportion of MMing days for the stocks in her portfolio is at least 20%. It means that such broker provides liquidity on at least one day of the week for half of the stocks she trades. This filter eliminates brokers with stock-days mistakenly categorized as MMing. Some stocks-days within a broker may look like MMing by chance, but the 20% threshold ensures exclusion of such brokers. Moreover, analyzing only stable MMing strategies facilitates their comparison when competition between liquidity providers suddenly changes. Since many brokers pursue a variety of strategies (e.g., O'Hara, 2015; Boehmer, Li, and Saar, 2018), some of them may abandon MMing in response to a changing market environment if it is not their core strategy. This decision may be driven by factors unrelated to liquidity provision profitability, which may complicate our analysis.

After identifying potential MMs based on their trading patterns, we search for external validation to confirm liquidity provision as their core strategy. In general, we expect a MM to profit from liquidity provision on most of her MMing days. Conversely, a broker serving as an agent for her clients may provide liquidity as a part of her cost-minimizing execution algorithms (Li et al., 2019). Since interaction between buying and selling clients through an agency is a zero-sum game, we do not expect this broker to profit from liquidity provision, i.e., we should observe approximately equal number of MMing days with profits and losses. Using this logic, our last filter excludes these agency brokers from the final list of MMs. We also check for any public information confirming liquidity providing activities of the brokers in the final list.

Finally, we categorize brokers in the final list as either slower or faster MMs based on their usage of the Chi-X exchange. Previous literature indicates that Chi-X caters its technologies to HFTs, e.g., by providing low latency (Chordia, Goyal, Lehman, and Saar, 2013; Menkveld, 2013, 2016). Moreover, some studies use the entry of Chi-X to new markets as an exogeneous instrument positively correlated with the level of HFT activity (e.g., Malceniece, Malcenieks, and Putniņš, 2019). Therefore, we identify slower and faster brokers by the extent they use Chi-X.

To sum up, the procedure that we employ for identifying MMs benefit from three information sources: proxies for non-directional passive trading, actual names of the brokers and descriptions of their activities, and analysis of their MMing profitability. For comparison, previous literature mostly relies on proxies for non-directional passive trading rather than profitability, since broker identities are rarely available for researchers (e.g., Malinova and Park, 2015; Malinova and Park, 2016; Comerton-Forde et al., 2018; Brogaard and Garriott, 2019).[7] Yet, our procedure shares the common limitation of not taking into account smaller proprietary trading firms who implement their MMing strategies through other brokers.

3.2. Profits from liquidity provision

We estimate gross profits ($AUD) and profitability of trades (%) in MMing stock-days for the brokers in the final list of MMs in the following way:

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[7] Papers that analyze profits from liquidity provision include Menkveld (2013), Brogaard, Hendershott, and Riordan (2014), Anand and Venkataraman (2016), and Brogaard et al. (2018). However, they do not use this information to filter out traders who do not earn money from MMing, since they focus on liquidity providers in general. The focus of our paper is on a subset of liquidity providers who make money from MMing, so we exclude execution algorithms that provide liquidity to minimize execution costs for buy-side institutions rather than to profit from this activity.

$$\$Profit_{b,s,d} = \left(VWAP\ Sell_{b,s,d} - VWAP\ Buy_{b,s,d}\right) \times min\left(Volume\ Bought_{b,s,d}, Volume\ Sold_{b,s,d}\right), \tag{2}$$

$$\%Profitability_{b,s,d} = \frac{VWAP\ Sell_{b,s,d} - VWAP\ Buy_{b,s,d}}{\left(VWAP\ Sell_{b,s,d} + VWAP\ Buy_{b,s,d}\right)/2}, \tag{3}$$

where *VWAP Buy* (*Sell*)$_{b,s,d}$ is the volume-weighted average price at which broker *b* buys (sells) stock *s* on day *d*. So, *\$Profits* measures the total gains from MMing during the day, whereas *%Profitability* captures the average return per trade on MMing stock-days.

Our method differs from the previous literature (e.g., Menkveld, 2013; Brogaard et al., 2014; Anand and Venkataraman, 2016; Brogaard et al., 2018) in several respects. First, we use only MMing stock-days to minimize contamination of liquidity provision profits by other trading strategies. This is important since many market participants use a combination of strategies at the same time (O'Hara, 2015; Boehmer et al., 2018). Second, we focus on brokers' intraday MMing profits without marking their net positions to the closing midquote. Here we prefer to stay agnostic about whether a MM ends each day with zero inventory or, if she does, how she unwinds it. Some MMs prefer to end the day "flat" in terms of risk rather than unwinding inventory completely (Malinova and Park, 2016).[8] Those who close their open positions overnight may do it during the day or outside trading hours (e.g., through dark pools or other brokers), which makes profit estimates sensitive to the mark-to-market reference point. We avoid these issues by concentrating on intraday profits. Finally, since we estimate profits only on MMing stock-days, we do not confine our focus to the limit orders. This approach implies that a MM may use market orders to close opened positions as a part of her liquidity provision strategy.

3.3. Natural experiments

We exploit two natural experiments: the improved connection speed to the ASX in 2012 as an exogeneous shock to speed competition among faster and slower traders, as well as the entry of Chi-X in 2011 that fragmented the Australian market. We use the first shock to test hypotheses 1–4 and the second shock to test hypotheses 5–6.

[8] Appendix A illustrates these two types of inventory management strategies based on two HFT MMs from our sample. Fig. 1A–2A show that inventory management and liquidity provision strategies of HFT MMs could vary quite substantially through time.

Our final list of MMs includes two HFT MMs that appear in the Australian market around the Chi-X entry in 2011.[9] This timing seems deliberate as the fastest traders benefit the most from fragmented markets and technological advances of Chi-X (Foucault and Menkveld, 2008; Menkveld, 2013, 2016). Therefore, we expect these HFT MMs be faster than any of the incumbent MMs.[10]

On April 2, 2012, the ASX introduced the ITCH data-feed protocol that increased the access speed to market information for a fee. The ITCH technology essentially provides an opportunity to track market quotes and all amendments to them in real time. However, it does not support order entry. Subscribers to ASX ITCH need another protocol—OUCH—to trade on the market and benefit from their access to the new technology. Fortunately, the OUCH protocol has already been in place on the ASX since February 2012, which makes the introduction of the ASX ITCH more valuable for fast traders. We expect HFT MMs to benefit most from this innovation since it directly caters to speed-sensitive traders.[11]

The introduction of ASX ITCH increases speed competition from faster MMs. We run the following regressions on MMing stock-days to test how this shock affects slower incumbent MMs' profits, round-trip trade profitability, and liquidity provision strategies:

$$\$Profit_{b,s,d} = \alpha + \beta\mathbb{1}(ASX\ ITCH)_d + \boldsymbol{\gamma Controls_{s,d}} + \delta_d + \varepsilon_{b,s,d}, \tag{4}$$

$$\%Profitability_{b,s,d} = \alpha + \beta\mathbb{1}(ASX\ ITCH)_d + \boldsymbol{\gamma Controls_{s,d}} + \delta_d + \varepsilon_{b,s,d}, \tag{5}$$

$$\%TickConstrTrades_{b,s,d} = \alpha + \beta\mathbb{1}(ASX\ ITCH)_d + \boldsymbol{\gamma Controls_{s,d}} + \delta_d + \varepsilon_{b,s,d}, \tag{6}$$

where $\%TickConstrTrades_{b,s,d}$ is the proportion of passive trading volume executed by slower incumbent broker *b* in stock *s* on day *d* when the bid-ask spread is constrained by the minimum tick size, and $\mathbb{1}(ASX\ ITCH)_d$ is the indicator variable that equals one after the introduction of the ASX ITCH, and zero otherwise. ***Controls*** is the vector of stock characteristics, which includes trading volume, volatility, liquidity measures, and the percentage of time the spread remains tick-constrained during the day. All regressions use day fixed effects and standard errors clustered by broker and stock.

[9] Appendix B illustrates these two types of inventory management strategies based on two HFT MMs from our sample.

[10] If incumbent MMs were fast, we would expect them to trade on Chi-X intensively. However, Section 6.1 shows that it is not the case: they keep trading almost entirely on the ASX.

[11] Goldstein, Kwan, and Philip (2018) discuss ASX ITCH and its effect on HFTs in detail.

Next, we use the Chi-X entry to the Australian stock market to test hypotheses 4–5. Chi-X entered the market on October 31, 2011, becoming the only competing lit venue to the ASX. Chi-X utilized the staggered introduction of trading in different stocks until it covered the full universe of ASX stocks on May 3, 2013. In our analysis we concentrate on the largest 200 stocks (henceforth, ASX200 stocks), which began trading on the entrant venue on November 9, 2011.[12] The Australian regulator leaves connection to Chi-X at a trader's discretion, which implies that only fast brokers with access to the SOR technology may easily exploit the new market. Therefore, we expect profits and trade profitability of HFT MMs to go up as Chi-X gains market share. We test this hypothesis by running the following regressions:

$$\$Profit_{b,s,d} = \alpha + \beta Chi\text{-}X\ market\ share_{s,d} + \boldsymbol{\gamma Controls_{s,d}} + \delta_d + \varepsilon_{b,s,d}, \tag{7}$$

$$\%Profitability_{b,s,d} = \alpha + \beta Chi\text{-}X\ market\ share_{s,d} + \boldsymbol{\gamma Controls_{s,d}} + \delta_d + \varepsilon_{b,s,d}, \tag{8}$$

where *Chi-X market share*$_{s,d}$ is the market share of Chi-X in the total dollar trading volume across exchanges for stock s on day d. This regression specification is analogous to the one used by Aitken, Chen, and Foley (2017) to study the effect of the Chi-X entry in Australia on market quality.

4. Data and descriptive statistics

4.1. Institutional setting

Our sample consists of 185 stocks from the ASX200 index that are traded on the ASX and Chi-X from January 1, 2011, to February 28, 2013. These stocks account for approximately 80% of the total value of Australian equities. The ASX and Chi-X are the only two stock exchanges operating in Australia during our sample period. Both of them are organized as transparent but anonymous central limit order books (CLOBs) with price-time priority rule for execution. The CLOBs are post-trade transparent: brokerage firms associated with each trade are revealed to the public three days after execution. The minimum tick size increment depends on the stock price: it is set to \$AUD 0.001 for prices below \$AUD 0.10, \$AUD 0.005 for prices between \$AUD 0.10 and \$AUD 2.00, and \$AUD 0.01 for prices above \$AUD 2.00. The lit CLOBs account for more than 75% of consolidated dollar volume, while the rest is executed through two exchange-operated dark venues (the ASX Centre Point dark pool and Chi-X dark orders) and around 21 broker-

[12] Aitken et al. (2017) discuss the entry of Chi-X in detail and investigate how it affects market quality.

operated dark pools (Foley and Putniņš, 2016).[13] Throughout our sample period the Chi-X market share does not exceed 7% of the overall exchange-traded dollar volume.

Neither ASX nor Chi-X adopt a make-take or inverted fee model when one of the counterparties in a trade pays a fee, while another receives a rebate. Both liquidity providers and demanders pay a fee for executing a trade. Chi-X charges providers less than demanders and ask for lower fees overall compared to the ASX (see Aitken et al., 2017). This is different from the US market, where different markets use different fee models. Yet, it is beneficial for the purposes of our study as we do not face additional complexities associated with competition between different fee schedules (see Comerton-Forde, Grégoire, and Zhong, 2019).

Similar to European markets, there is no "trade through" prohibition in Australia. It means that a broker is not required to route the client's order to the market with the best available quote like in the US. Although the Australian regulator requires brokers to ensure the best execution for clients' orders, "best execution" is not strictly determined and could include such characteristics as "speed, likelihood of execution, and any other relevant characteristics"[14]. As a result, connection to Chi-X remains at the broker's discretion in Australia. In this situation, liquidity providers could potentially jump ahead of the BBO queue in one market by posting price-improving quotes to another market.

4.2. Data

Our data allows to track trades of broker accounts registered with the Australian regulator on all exchanges (lit and dark venues operated by the ASX and Chi-X) throughout the day (inside and outside normal trading hours). These accounts represent brokers who can act as proprietary traders, execute trades on behalf of others, or both. Those who trade on their own are likely to use their own broker accounts since trading through other brokers involves additional fees and complicates security settlements, which increases the amount of capital needed for trading strategies.

We download the millisecond-stamped data on ASX trades from the AusEquities database maintained by the Securities Industry Research Centre of Asia-Pacific (SIRCA). Each trade is

[13] Comerton-Forde and Putniņš (2015), Foley and Putniņš (2016), and Aitken et al. (2017) provide more details on the institutional setting around lit and dark trading in Australia.

[14] See Section G of "Guidance on ASIC market integrity rules for participants of securities markets" (Regulatory Guide 265), Australian Securities & Investment Commission, May 2018.

assigned with several identifiers: buyer and seller broker IDs, whether a trade is initiated by a buyer or seller, call auction and off-market trade identifiers, and others. We match broker IDs with the lists of brokerage company names, publicly released by the ASX. The similar data on Chi-X trades comes directly from Chi-X Australia. We supplement the trading data with ASX intraday quotes from AusEquities, Chi-X intraday quotes from the Thomson Reuters Tick History (TRTH) database, daily pricing and volume data from TRTH, and daily data on shares outstanding and adjustment factors from the Morningstar Corporate Actions database.[15]

There are 96 brokers trading on the ASX in our sample period. They participate in 95.02% (96.57%) of all trades (dollar volume) executed on Chi-X. For simplicity, we focus only on these 96 brokers in our analysis. Following Goldstein et al. (2018) and Upson, McInish, and Johnson (2018) we aggregate brokers' marketable orders in each stock at the same time, price, and trade direction into a single marketable order. Then we pull the ASX and Chi-X trades of each broker together in chronological order for the main analysis.

4.3. Descriptive statistics

Table 1 reports descriptive statistics for the final sample of 185 stocks and 96 brokers. Panel A indicates that an average stock in our sample has a market capitalization of $AUD 6,459.59 million, a price of $AUD 8.25, and is associated with $AUD 24.95 million trading volume on a typical day. The average quoted, effective, and 30-second realized spreads equal to 32.29, 31.29, and 10.17 basis points, respectively, whereas the average 30-second price impact is at 19.41 basis points. Most stocks in our sample are characterized by the bid-ask spreads equal to a single tick, with an average (median) stock being tick-constrained for 85.30% (92.41%) of the time during the day. Thus, the average (median) stock in our sample has around 52.92 (27.32) minutes during the day for potential price improvements. So, price competition in the ASX200 stocks is restricted most of the time.

Panel B of Table 2 shows that an average (median) broker in our sample trades 73.79 (53.00) stocks per day, which corresponds to $AUD 126.64 million ($AUD 15.51 million) daily trading volume. On an average day, brokers are passive 47.61% of the time and have an absolute end-of-day buy-sell order imbalance of 58.88%. Such order imbalance is more consistent with

[15] We thank SIRCA for providing access to the listed databases.

directional trading strategies, implying that the usage of limit orders may not be a single reliable factor to identify MMing strategies.[16]

< Table 1 here >

Next, we identify MMs with the procedure outlined in Section 3.1. Panel A of Table 2 summarizes the results of this procedure. We find 86 brokers that have at least one stock-day classified as MMing according to the broker's order imbalance (within 30%) and proportion of passive trading volume (at least 50%). For each broker we calculate the proportion of days per stock classified as MMing and filter off brokers with the median proportion below 20%. As a result, we have 12 potential MMs that provide liquidity on at least one day of the week for half of the stocks in their portfolios. From this list of potential MMs we want to find those who provide liquidity for profit. The official websites of the three potential MMs and popular business press indicate that they make markets in many countries, which is a reasonable external validation of their profitable MMing activities. Two of these MMs are well-known international HFT firms, which enter our sample in June and November 2011.[17] Next, we estimate dollar profits earned by each of the 12 potential MMs on MMing stock-days as in Eq. (2) and aggregate these profits for each MMing day. To alleviate the effect of the HFT MMss entry to Australia on profits from liquidity provision, we only consider the time period before the entry of the first HFT MM. We find three brokers earning stably positive profits (at least 60% of the days are profitable), with one of them being externally validated as MM through public information sources described above. As these brokers appear in our sample earlier than two HFT MMs, we call them incumbent MMs. Two HFT MMs also earn stably positive profits during our sample period. Therefore, our final list of MMs consists of five brokers providing liquidity for profit on a regular basis.

Panel B of Table 2 reports the selected characteristics of the five MMs from the final sample. All brokers have above-median daily trading volume and trade on both the ASX and Chi-X. Yet, two MMs recognized as HFT MMs above use the new market much more extensively:

[16] Usage of order imbalance alone might not be a good alternative either. Aggressive HFTs that exploit short-lived arbitrage opportunities prefer to keep low order imbalance while using mostly marketable orders (Brogaard and Garriott, 2019).

[17] We treat the first time we observe trades of these HFT MMs under their own brokerage account as the entry time to Australia, althuogh they could have started trading through other brokers earlier.

in aggregate they contribute more than 80% (40%) to the passive (total) trading volume on the entrant venue vs. less than 10% (10%) for the leftover MMs.[18] This fact confirms that these two MMs are HFT MMs, since HFTs should be the ones benefitting from using Chi-X due to its advanced technologies designed for fast traders (Chordia et al., 2013; Menkveld, 2013, 2016). Henceforth we call these MMs "HFT MMs" and call the rest three brokers "slower incumbent MMs". HFT MMs are more active liquidity providers compared to incumbent MMs: they make markets on 52.25%–54.09% of the days on which they trade a particular stock compared to 20.42%–32.24% for incumbent MMs. HFT MMs provide liquidity for 67.42–74.04 stocks in their portfolio, which constitute 43.95%–61.86% of the stocks they trade on an average day. Incumbent MMs are less active in this respect: they make markets for 33.58–50.44 stocks on an average day, which corresponds to 21.03%–31.35% of their portfolios. Moreover, HFT MMs are more active at their inventory management, with their cumulative position switching between long and short for more than ten times within a MMing day. However, most incumbent MMs enjoy higher trade profitability while MMing compared to HFT MMs, indicating that the latter may incur higher adverse selection costs during liquidity provision. Nevertheless, HFT MMs are profitable on 83.88%–88.96% of the days, whereas incumbent MMs experience a drop in the proportion of profitable days after the HFT MM 1 entry (the higher figures in brackets represent the proportion of profitable days before the entry).

< Table 2 here >

Fig. 1 illustrates the cumulative market share of five MMs in total and passive trading volume on the ASX and Chi-X. MMs' market share on the entrant market is much larger compared to that on the incumbent market due to the influence of HFT MMs. The blue solid area in Panel D (Panel C) indicates that the cumulative market share of five MMs in passive (total) trading volume on Chi-X is around 80% (30%), but only 10% (5%) on the ASX as illustrated in Panel B (Panel A). Overall, contribution of MMs to the total amount of liquidity provided in Australia appears modest relative to other brokers.

[18] We illustrate each broker's usage of Chi-X through time in Fig. 4–5 (Section 6.1 discusses these figures in detail). The plots confirm consistent extensive usage of Chi-X by the two MMs from our sample.

Interestingly, more than 50% of the passive volume on the ASX comes from seven brokers that are identified as potential MMs but do not qualify to the final list of MMs due to approximately equal number of profitable and unprofitable MMing days (see Panel B of Fig. 1 and Table B1 of Appendix B). We call these brokers "quasi MMs" as they do not make stable profits from their MMing activity. These brokers represent large investment banks with an average daily trading volume of $AUD 461.08–1,416.90 (Table B1 of Appendix B provides more detailed characteristics on each of the quasi MMs). The main business of these brokers is execution of trades for their clients, which might explain why they do not profit from liquidity provision. As Li et al. (2019) explain, buy-side institutions may provide liquidity as a part of their cost-minimizing execution algorithms, without pursuing an MMing strategy in a traditional sense (i.e., earning the spread). The large market share of quasi MMs in passive trading volume observed in Fig. 1 (Panel B) is indicative of a substantial amount of liquidity provided outside traditional MMing strategies.

< Fig. 1 here >

5. Main results

5.1. ASX ITCH introduction

On April 2, 2012, the ASX introduced the ITCH data-feed protocol that increased the access speed to market information for a fee. We expect HFT MMs to benefit most from this innovation since it directly caters to speed-sensitive traders. This event raises speed competition from faster traders faced by slower incumbent MMs, allowing us to test hypotheses 1–4. We do it by running regressions as in Eq. (4)–(6) for our sample of the three incumbent slower MMs with $\mathbb{1}$(*ASX ITCH*) as the main explanatory variable that equals one after the introduction of the ASX ITCH technology, and zero otherwise. Control variables include the log *Volume*, *Volatility*, *Tick-constrained*, and *Effective spread* defined as in Table 1.[19] We also use day fixed effects to control for time-varying factors that might affect profits from liquidity provision.

Table 3 reports the results. Columns (1)–(2) indicate that the introduction of the new speed technology translates into $AUD 803–885 drop in stock-day profits for slower incumbent MMs after controlling for confounding factors. This drop is statistically and economically significant,

[19] All results remain qualitatively similar if we replace equal-weighted effective spread with volume-weighted effective spread, time-weighted quoted spread, or Amihud (2002) illiquidity measure.

with the *t*-statistics of 2.170-2.172 and the total daily value of forgone profit reaching \$AUD 32,120–35,400 (given that an average incumbent MM makes markets for around 40 stocks per day, see Table 2). In columns (3)-(4) we repeat the analysis for a shorter five-month window before and after the introduction of the ASX ITCH technology. We choose this time window because both HFT MMs enter the Australian market five months before the ASX ITCH event. The results return similar coefficients on $\mathbb{1}$(*ASX ITCH*), although we lose statistical significance due to a smaller number of observations.

Column (5) of Table 3 shows that round-trip trade profitability from MMing hardly changes. We observe marginally significant coefficient on $\mathbb{1}$(*ASX ITCH*), which loses its statistical and economical power when we control for confounding factors in column (6). These results support hypotheses 1 and 2b: increased speed competition from faster MMs decrease dollar profits but not profitability of slower MMs.

These results may be driven by two alternative scenarios. On the one hand, slower incumbent MMs might incur additional adverse selection after the introduction of the new speed technology. Then they may start posting limit orders with lower execution probability as in Hoffman (2014), which could maintain trade profitability at the pre-event level at the expense of lower proportion of volume executed when the bid-ask spread is constrained by a single tick. On the other hand, if the HFT MM does not expose incumbent MMs to additional pick-off risks we should not see a drop in the amount of volume executed in a tick-constrained environment. We distinguish between the two scenarios by regressing the proportion of passive trades executed when the bid-ask spread is constrained by the minimum tick size on ASX ITCH indicator variable and control variables as in Eq. (6). Columns (9)–(10) of Table 3 report the results. Neither univariate nor multivariate regressions show a negative effect of increased speed competition on the proportion of passive trades executed at the tick-constrained prices. If anything, column (10) suggests that slower incumbent MMs experience a 7% spike in the proportion of passive volume executed when the bid-ask spreads is tick-constrained after controlling for confounding factors. These findings confirm hypothesis 4b.

< Table 3 here >

Next, we analyze the impact of the ASX ITCH introduction on HFT MMs. If HFT MMs use their speed advantage for liquidity provision, we expect them to generate additional profits from MMing after implementation of the new speed technology. By separately looking at the fast MMs' dollar profits and round-trip trade profitability, we can further test the mechanism of queuing at the BBO that restricts fast traders from canceling their quotes to preserve their time priority. If the latter is the case, HFT MMs should absorb most of the adverse selection without transferring it to the slower incumbent MMs staying behind in the queue. Therefore, the ASX ITCH introduction should help HFT MMs to raise their dollar profits but not round-trip trade profitability. We test the effect of the ASX ITCH on HFT MMs by running regressions as in Eq. (4)–(5) for the two HFT MMs in our sample.

Table 4 reports the results. The positive and significant coefficients on the ASX ITCH dummy in columns (1)–(2) indicate that HFT MMs earn more dollar profits after the implementation of the new technology. After controlling for the confounding factors, an average HFT MM earns $AUD 460 more per MMing stock-day. Given that an average HFT MM makes markets for approximately 71 stocks per day (see Table 2), it translates into a significant daily gain of $AUD 32,660. If we limit the sample period to the five months before and after the event, we still document a significantly positive effect of the ASX ITCH introduction on dollar profits of HFT MMs as can be seen in column (4). This effect is less economically and statistically significant, suggesting that it might take a while until HFT MMs exercise their speed advantage to put their MMing algorithms to their best use.

Columns (5)–(8) of Table 4 indicate that the trade profitability of HFT MMs does not significantly change after the implementation of the new technology. It means that HFT MMs do not pay additional adverse selection costs after implementation of the new speed technology, which is not consistent with the queuing mechanism. Yet, it is not surprising since increased opportunities for realizing comparative speed advantage that come with the ASX ITCH incentivize HFT MMs to enter the market, thus intensifying competition among faster MMs.[20] We expect fast MMs to bear more adverse selection risks in the short-term, which allows them to keep their front

[20] Although we identify only two HFT MMs in our sample, we expect more HFT MMs to enter the market after the introduction of ASX ITCH. Unfortunately, we may not recognize them in the data if they are not big enough and trade through other brokers. Small HFT MMs that are not registered as brokers with the Australian regulator can still access the ASX ITCH technology by sharing the co-located facilities with their brokers (see, e.g., "ASX co-location racks leasing fast", itnews, April 15, 2013).

queue positions. In fact, if we limit our sample to a shorter time period—three months before and after the ASX ITCH—we observe more negative and statistically significant coefficients on the ASX ITCH dummy. In columns (7)-(8) we also observe negative but statistically insignificant coefficients for the ASX ITCH effect in the first five months. But in the long run the number of fast MMs exercising their speed advantage for liquidity provision would increase, allowing to share the adverse selection risks between each other, which explains insignificant positive coefficients in columns (5)-(6).

< Table 4 here >

Our results so far demonstrate the increased role of speed in liquidity provision, which brings more dollar profits to HFT MMs at the expense of slower incumbent MMs. The statistical power of our tests often remains weak due to a small number of brokers in the sample. However, there is a chance that our findings are driven by spurious correlations due to the measurement error in *$Profit* and *%Profitability*. To alleviate this concern, we conduct a placebo test. Specifically, we run regressions as in Eq. (4)–(5)—similar to what we did in Tables 3 and 4—for the sample of quasi MMs who do not earn profits from liquidity provision. If our results arise by chance, then we expect to see some significant coefficients in the placebo test as well.

Table 5 reports the results. All coefficients on the ASX ITCH dummy are reliably insignificant with the *t*-statistics below 1.000. Moreover, the coefficients on all other confounding variables that may affect *$Profit* and *%Profitability* are also insignificant in all regression specifications. For comparison, regressions on the samples of HFT MMs and slower incumbent MMs in Tables 3 and 4, respectively, both show a few variables significantly affecting dollar profits and trade profitability. Therefore, the placebo test provides additional support for our findings.

< Table 5 here >

Overall, our results indicate that the transit of the MMing function towards HFTs let the slower MMs survive and still earn some money from liquidity provision. New technology favors HFT MMs' comparative speed advantage utilized for making money from liquidity provision. The increased competition from faster traders erode dollar profits of incumbent MMs but does not expose them to increased adverse selection, leaving their trade profitability unaffected. The latter allows slower traders to maintain their MMing business, which should lead to an overall improvement of market liquidity as predicted by Aït-Sahalia and Sağlam (2017).

5.2. Adverse selection channel

Our results are consistent with slower incumbent MMs not incurring additional adverse selection costs when speed competition increases. So far, we focus on the realized dollar profits and percentage round-trip trade profitability from MMing rather than on existing proxies of adverse selection. Next, we look at the traditional spread measures—realized spread and price impact—to test the adverse selection channel from another perspective.

Realized spread and price impact measure the temporary and permanent price changes after a trade. They are calculated as follows:

$$Realized\ spread_{s,t,x} = 2 \times d_{s,t} \frac{p_{s,t} - m_{s,t+x}}{m_{s,t}}, \tag{9}$$

$$Price\ impact_{s,t,x} = 2 \times d_{s,t} \frac{m_{s,t+x} - m_{s,t}}{m_{s,t}}, \tag{10}$$

where $d_{s,t}$ equals +1 for buyer-initiated trades and –1 for seller-initiated trades in stock s at time t, $p_{s,t}$ is the transaction price, $m_{s,t}$ is the prevailing midpoint price (i.e., the midpoint between the ask and bid quotes just before the trade), and $m_{s,t+x}$ is the midpoint price at time $t+x$ after the trade. In Realized spread and price impact reflect *nominal* profit to liquidity providers and permanent price change some time after the trade, respectively. These measures are nominal because they are not capturing actual MMign strategies and simply assume that a MM closes an opened liquidity-providing trade with a limit order exactly at time $t+x$ after the trade, and there is no temporary price pressure left in the midquote at time $t+x$.[21] Nevertheless, realized spread and price impact reflect the nominal percentage profitability and adverse selection risk borne by a MM shortly after the trade. We use these measures to investigate the adverse selection channel at a closer range.

[21] Conrad and Wahal (2019) document high sensitivity of realized spread and price impact measures to the choice of the trading horizon, $t+x$. In this sense, our MMing profit measures are better reflecting the diverse set of strategies employed by MMs as they account for the actual time when opened positions are closed.

We investigate what happens with realized spread and price impact of slower incumbent MMs after the ASX ITCH introduction. Following Eq. (9)–(10) we calculate realized spread and price impact 30 seconds after each passive trade executed by a MM in a MMing stock-day.[22] Then, we calculate the equal-weighted average realized spread and price impact for all trades executed by a broker in a stock-day separately for the two subsamples of trades.[23] The first subsample consists of trades that occur when the bid-ask spread is tick-constrained and the seconds subsample considers trades that happen when the spread is tick-*un*constrained. We run the following regressions separately for the two subsamples of trades:

$$Realized\ spread_{b,s,d} = \alpha + \beta \mathbb{1}(ASX\ ITCH)_d + \boldsymbol{\gamma Controls_{s,d}} + \delta_d + \varepsilon_{b,s,d}, \quad (11)$$

$$Price\ impact_{b,s,d} = \alpha + \beta \mathbb{1}(ASX\ ITCH)_d + \boldsymbol{\gamma Controls_{s,d}} + \delta_d + \varepsilon_{b,s,d}, \quad (12)$$

where control variables include previous-month average daily price volatility and natural logarithm of trading volume (in $thousands), as well as the closing price at the end of the previous month (all defined as in Table 1). If our conjecture on the role of restricted price competition in adverse selection transfer from faster and slower MMs is correct, we expect to see no change in realized spreads and price impacts in a tick-constrained environment. Conversely, if the bid-ask spread is not restricted by the minimum tick increment, we expect to see decreased realized spreads and increased price impacts.

Panel A of Table 6 reports the results for the passive trades executed in a tick-constrained environment. Insignificant coefficients on the ASX ITCH dummy in columns (1)–(4) indicate no change in realized spreads for slower incumbent MMs, consistent with our previous results on round-trip trade profitability. Price impacts do not change either as evident from columns (5)–(6), suggesting that the passive trades of incumbent MMs do not bear additional adverse selection risk, albeit this result is not robust to a shorter time period around the ASX ITCH introduction as shown in columns (7)–(8). Conversely, Panel B reports the opposite results for passive trades executed in a tick-unconstrained environment. Columns (1)–(2) and (5)–(6) report a significant drop in 30-second realized spreads and a significant spike in a 30-second price impacts, consistent with increasing adverse selection costs borne by slower MMs after increased competition from HFT

[22] Our results are robust to using other trading horizons (1 second, 10 seconds, 1 minute, and 5 minutes)
[23] Our results are robust to using volume-weighted realized spreads and price impacts.

MMs. These results indicate that the restricted price competition can also limit the ability of faster MMs to transfer adverse selection risks on other traders.

< Table 6 here >

We conduct a similar analysis for HFT MMs in Table 7. These results should be treated with caution because the ASX ITCH technology is a good incentive for other HFT MMs to enter the market.[24] As a result, increased adverse selection right after the ASX ITCH introduction might decrease in the long run as more HFT MMs enter the Australian market. Panel A confirms this intuition. Columns (2) and (4) indicate that realized spreads are decreasing in a tick-constrained environment, after controlling for confounding factors. At the same time, price impact is increasing in the short run and decreasing in the long run as reported in columns (8) and (6), respectively. This is consistent with first HFT MMs bearing more adverse selection risk initially, but not in the long run as new HFT MMs enter the market. Panel B shows similar results for the tick-unconstrained environment. It might be driven by incoming fast traders incentivized by the introduction of the new technology, which makes the interpretation of the results for HFT MMs in this case more problematic.

< Table 7 here >

6. Additional analysis

This section investigates the additional structural market change that happens during our sample period and discusses the results of the paper in a broader context of policies regulating speed and price competition in financial markets.

6.1. Fragmentation

On November 9, 2011, the ASX200 stocks that constitute our sample began trading on Chi-X, making the market environment more fragmented. HFT MMs can benefit from this change as they usually possess the SOR technology needed to exploit opportunities on both markets. At the same time, we expect incumbent MMs to stick to the ASX due to the lack of relevant technologies.

[24] Footnote 20 discusses the issues with identifying other HFT MMs in the sample.

We test how fragmentation affects dollar profits and trade profitability of HFT MMs and incumbent MMs.

We begin with testing our conjunction on possession of smart routers by HFT MMs and incumbent MMs. With this technology at hand, a trader should send orders to the market with more favorable quotes. When it comes to liquidity provision, a MM can skip time priority in the incumbent market by jumping ahead of queue to the entrant market. Thus, if a MM possesses a smart router, we should see her occasionally trading on the new market.

Fig. 2 and 3 plot the proportion of total and passive trading volume executed on the ASX and Chi-X by each broker. Panel A of Fig. 2 indicates that from 2012 HFT MM 1 executes around 70% of the total trades and almost all of her passive orders on the entrant market. Likewise, HFT MM 2 trades 30%–40% of the time on Chi-X, with 10% to 70% of the passive volume executed on the entrant market (Panel B). Such intensive usage of Chi-X for trading and liquidity provision confirms HFT MMs' possession of the relevant technologies for exploiting both markets.

When it comes to incumbent MMs, Fig. 3 demonstrates that they do not use Chi-X that much. Incumbent MM 1 has a negligible amount of trading on the entrant market (Panel A); incumbent MM 2 executes less than 5% of her trades by the end of the sample period (Panel B); and incumbent MM 3 routes approximately 10% of her trades to Chi-X by the end of the sample period (Panel C). So, incumbent MMs seem to use the SOR technology less intensively, suggesting that their benefits from the entrant market may be limited.[25]

< Fig. 2 here >

< Fig. 3 here >

Next, we examine the effect of increased fragmentation on the dollar profits and trade profitability of fast and slow traders. We run regressions as in Eq. (7)–(8) for the period starting from November 9, 2011, separately for the HFT MMs and incumbent MMs. The market share of Chi-X in a total trading volume for a stock serves as the main explanatory variable.

Columns (1)–(2) of Table 8 show that HFT MMs enjoy higher dollar profits from the higher Chi-X market share. However, the economic significance is modest: after controlling for

[25] Given "symbiotic" relationship between Chi-X and HFTs (Menkveld 2013, 2016), the intensive (limited) usage of Chi-X is another evidence of the identified MMs being faster (slower) than other MMing brokers.

confounding factors, 1% increase in the Chi-X market share is associated with less than $AUD 4 increase in a stock-day profit. Given that the market share of Chi-X does not exceed 7% during our sample period, this effect is economically small. Similarly, we observe only a modest increase in trade profitability equals to 0.103 basis points for every additional percentage of the Chi-X market share. These results are consistent with HFT MMs making additional money from routing their orders to the entrant market to jump ahead of the limit order queue in the incumbent market.

Columns (5)–(8) of Table 8 report results for the incumbent MMs. Neither of the coefficients on the Chi-X market share is significant, indicating that incumbent MMs do not benefit from the increased fragmentation.

< Table 8 here >

Overall, the results in Table 8 support hypotheses 5–6: HFT MMs enjoy increased dollar profits and trade profitability from fragmented markets, whereas incumbent MMs do not benefit from it. Yet, the documented positive effect for HFT MMs is economically small. These results most likely arise due to a modest market share of Chi-X during our sample period, which may disincentivize market participants to invest into the SOR technology to access Chi-X in line with theoretical predictions in Foucault and Menkveld (2008). So, we expect the statistical and economic effect to vanish as more the new trading venue increases its market share.

6.2. Discussion

Competition on speed has been in the focus of the recent theoretical research (e.g., Hoffman, 2014; Biais e al., 2015; Budish et al., 2015; Foucault et al., 2017; Menkveld and Zoican, 2017; Aït-Sahalia and Sağlam, 2017; Li et al., 2019). Hoffman (2014), Biais et al. (2015), Budish et al. (2015), and Menkveld and Zoican (2017) among others, demonstrate that the current level of advancement in speed technology may not be socially optimal. As Paul Krugman, the 2008 Nobel laureate in Economics, once put it in words while commenting on the new fiber-optic cable connecting Chicago and New York "spending hundreds of millions of dollars to save three milliseconds looks like a huge waste".[26] Yet, market participants have clear incentives to invest in speed. Specifically, by becoming faster liquidity providers can ensure a better position in the limit

[26] See "Three Expensive Milliseconds", The New York Times, April 13, 2014.

order queue and decrease additional adverse selection costs by timely canceling their stale quotes (Hoffman, 2014; Han et al., 2014; Bongaerts and van Achter, 2016; Aït-Sahalia and Sağlam, 2017; Bernales, 2019). Therefore, unless facing additional barriers to implement high-frequency trading strategies, market participants would invest in speed.[27]

However, there is a way to put ubiquitous speed advancements to their best use for society without constraining them. Aït-Sahalia and Sağlam (2017) show that the long limit order queue at the BBO arisen in a tick-constrained environment forces HFT MMs to limit their order cancelation activity and bear most of the adverse selection risk in the market. It means that the transfer of liquidity provision profits from slower to faster MMs is accompanied by relieving slower market participants from bearing additional adverse selection costs. Our findings confirm this intuition. We show that increased speed competition shifts MMing dollar profits from slower to faster MMs without imposing the latter to decreased trade profitability. It implies that the restricted price competition—in a form of a minimum tick size—might be beneficial for the overall market liquidity as it may induce HFT MMs to incur most of the adverse selection risk in the market.

7. Conclusion

We investigate how the increased role of speed changes competition among liquidity providers. We document the shift in liquidity provision from slower to faster MMs. Changes that happen in the Australian market—specifically, the increased connection to the ASX—favor HFT MMs, whose dollar profits from liquidity provision increase. However, these changes negatively affect slower incumbent MMs, who lose their time priority in the limit order queue and start to earn less money from MMing. Nevertheless, their trade profitability does not significantly change, which means that incumbent MMs can survive and still contribute to liquidity provision in the market.

Our results imply that unrestricted speed competition under tick-constrained environment may increase liquidity by inducing HFT MMs to absorb most of the adverse selection risk in the market to reserve their time priority in the limit order queue. It means that slow and fast MMs can co-exist consistent with the model of Aït-Sahalia and Sağlam (2017).

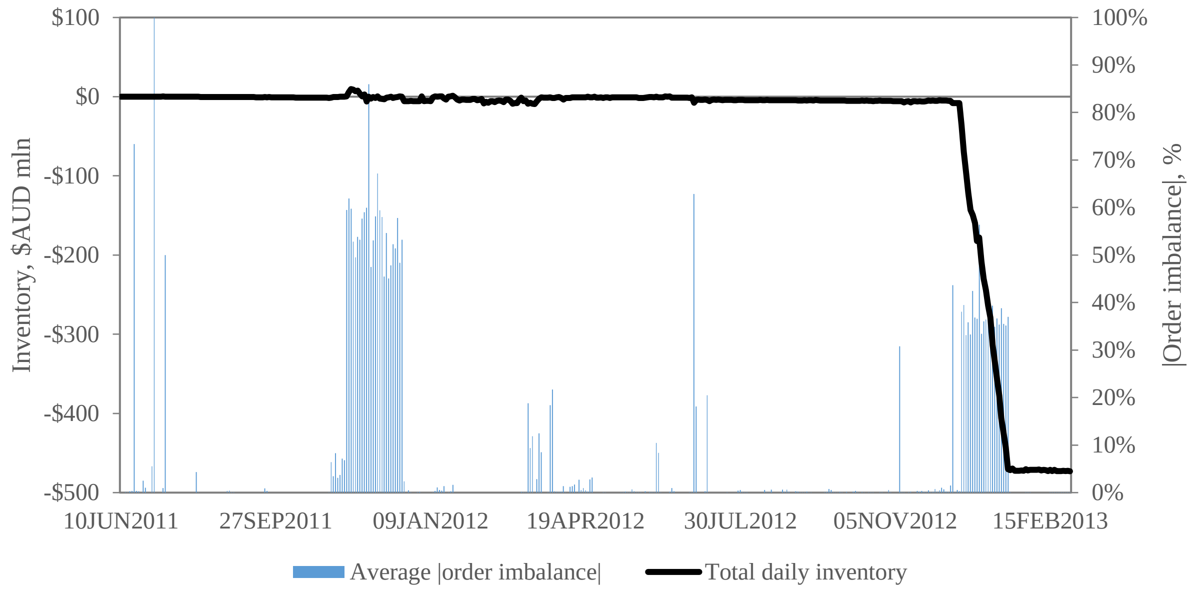
[27] Aït-Sahalia and Sağlam (2017) discuss the implementation of regulations and market mechanisms restricting HFT activity in different countries.

Regulators in many countries are concerned about the value HFTs bring to the market. Many European countries have already implemented some policies to limit the HFT activity. Yet, these policies are not always beneficial for other market participants. Malinova, Park, and Riordan (2018) document that such policy implemented in Canada in 2012 led retail investors and institutions to pay much larger cost for executing their trades. Restricting price competition by setting the right tick size could be an alternative option that does not limit HFT activity but encourages faster MMs to bear adverse selection costs, which would otherwise be borne by other market participants.

Appendix A: Inventory management and liquidity provision of HFT MMs

We observe two HFT MMs that enter the Australian market during our sample period. We track all their trades on the ASX and Chi-X, including dark trades on exchange-operated platforms (see Section 4.1 for details). We compute their dollar inventory across all stocks throughout our sample period. Panel A of Fig. A1 shows that the first HFT MM prefers to end each day with zero inventory and keeps order imbalance of stocks at zero levels most of the time. Conversely, the second HFT MM in Panel B has a substantial amount of inventory at the end of most days but keeps her order imbalance across stocks under control as it rarely exceeds 30%. The two styles of inventory management that we observe in Panels A and B of Fig. A1 resemble the two ways of keeping overnight inventory under control—end the day "flat" in terms of either holdings or risk—described in Malinova and Park (2016).

Panel A: HFT MM 1



Panel B: HFT MM 2

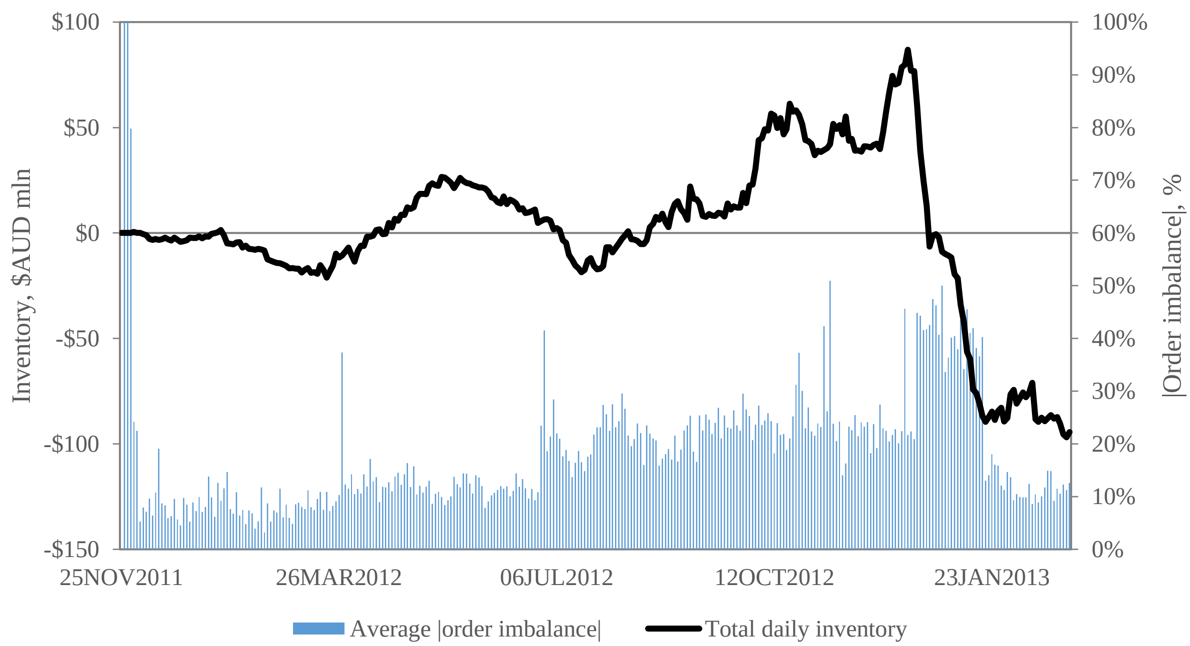
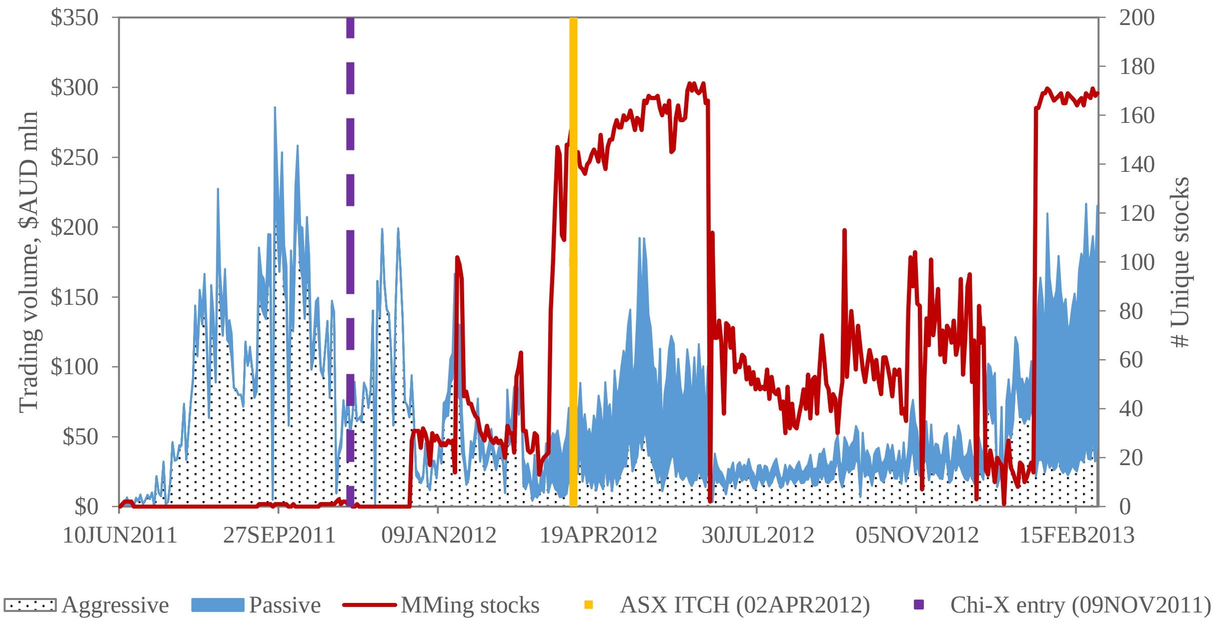


Fig. A1. Inventory management of HFT MMs. The figure plots the cumulative daily dollar inventory position (black solid line, left axis) and average daily absolute order imbalance across stocks (blue bars underneath, right axis) for the two HFT MMs in our sample. The sample period starts from the time the HFT MMs first appear in the data (June 10, 2011, and November 25, 2011) until the end of the sample period (February 28, 2013).

Panel A: HFT MM 1



Panel B: HFT MM 2

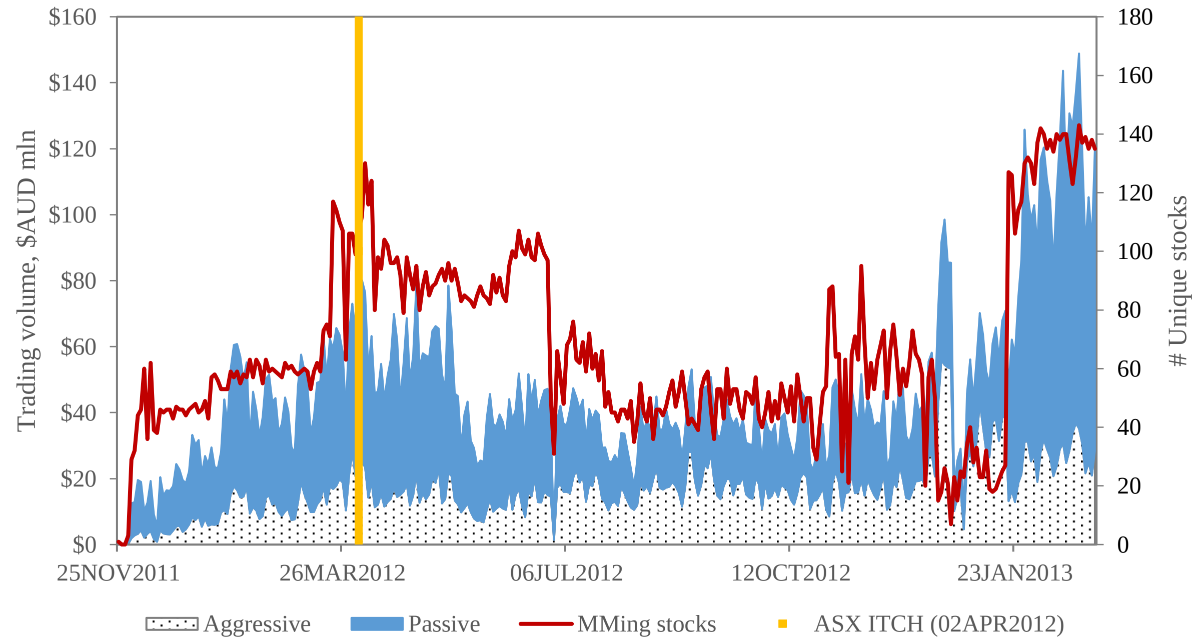


Fig. A2. **Provision of liquidity by HFT MMs.** This figure plots the evolution of liquidity provision by two HFT MMs from the time they appear in the data until the end of the sample period (February 28, 2013). The blue solid area represents the passive dollar trading volume executed by a HFT MM. The black dotted area represents the aggressive dollar trading volume executed by a HFT MM. The red solid line plots the number of unique stocks, in which a broker makes markets according to the MMing criteria defined as in Table 2. The purple dashed and orange solid vertical lines donote the time of the Chi-X entry (November 9, 2011) and ASX ITCH introduction (April 2, 2012).

Appendix B

Table B1
Characteristics of quasi market-making brokers
This table reports the selected characteristics for the seven quasi market-making brokers. These brokers are identified as potential MMs, but do not qualify to the final list of MMs due to insufficient number of profitable MMing days. We describe the procedure for MM identification in Section 3.1, with more details in Section 4.2 and Table 2. All variables are defined as in Table 2.

	Quasi MM 1	Quasi MM 2	Quasi MM 3	Quasi MM 4	Quasi MM 5	Quasi MM 6	Quasi MM 7
General characteristics							
Daily volume, $AUD mln	639.00	1,188.78	718.04	1,416.90	561.82	712.91	461.08
	(590.92)	(1,109.79)	(664.83)	(1,234.17)	(533.14)	(588.95)	(419.23)
Overall/Chi-X market share in total trading volume, %	6.99/11.04	12.24/4.37	7.78/12.53	14.99/8.57	5.77/13.90	7.69/2.10	3.95/9.96
	(4.79/5.20)	(9.49/1.59)	(5.03/5.04)	(12.34/2.67)	(4.08/8.46)	(4.84/0.76)	(1.77/4.70)
Overall/Chi-X market share in passive trading volume, %	10.52/5.63	13.02/1.01	8.59/2.34	17.40/17.7	9.28/4.14	7.82/0.72	4.51/2.60
	(8.62/1.12)	(11.13/0.00)	(6.52/0.00)	(16.58/3.95)	(7.61/0.00)	(5.82/0.00)	(2.34/0.00)
Market-maker characteristics							
% MMing days per stock	39.66	30.45	23.57	43.36	26.92	25.18	22.11
	(38.46)	(32.90)	(20.00)	(43.41)	(26.57)	(25.05)	(20.15)
% MMing stocks per day	40.13	30.64	23.83	43.70	27.65	25.81	22.84
	(38.24)	(31.21)	(22.42)	(42.44)	(25.43)	(23.46)	(19.32)
# MMing stocks per day	68.79	52.74	41.02	74.92	47.58	44.26	38.27
	(65.00)	(54.00)	(38.00)	(73.00)	(43.00)	(40.00)	(32.00)
# Times inventory crosses zero	2.34	2.33	2.64	3.30	2.48	1.68	1.49
	(1.00)	(1.00)	(1.00)	(2.00)	(1.00)	(1.00)	(1.00)
MMing trade profitability, bps	2.55	0.71	5.27	1.98	5.33	5.81	4.23
	(0.54)	(0.63)	(1.95)	(1.17)	(1.16)	(1.74)	(1.38)
% profitable days	51.10	63.30	55.60	48.35	52.66	43.49	57.43
	(43.12)	(56.88)	(52.29)	(53.21)	(45.87)	(47.71)	(55.96)

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Table 1
Descriptive statistics
This table reports descriptive statistics for the ASX200 stocks in our final sample (185 stocks in total) and 96 brokers trading these stocks (see Section 4.1 for details). The sample period is from January 1, 2011, to February 28, 2013. Panel A shows distribution of the stock-day variables. *MCap* and *Price* are based on the ASX closing prices. *Volume* represents the total dollar trading volume on the ASX and Chi-X. *Volatility* is the dollar volume-weighted price variability across the ASX and Chi-X, with the price variability equal to the difference between the highest and lowest prices during the day divided by the midpoint between the two prices. *Quoted spread* is the time-weighted relative quoted bid-ask spread consolidated across the ASX and Chi-X. *Effective spread* is the equal-weighted relative effective spread, calculated as the difference between the trade execution price and the prevailing midpoint bid-ask price at the time of execution (and standardized by the midpoint bid-ask price) separately for the ASX and Chi-X, and then dollar volume-weighted across exchanges. *Realized spread* (30 sec) is the equal-weighted relative realized spread, calculated as the difference between the trade execution price and the midpoint bid-ask price 30 seconds after execution (and standardized by the midpoint bid-ask price at the time of execution) separately for the ASX and Chi-X, and then dollar volume-weighted across exchanges. *Price impact* (30 sec) is the equal-weighted relative price impact, calculated as the difference between the midpoint bid-ask prices at the time of trade execution and 30 seconds after execution (and standardized by the midpoint bid-ask price at the time of execution) separately for the ASX and Chi-X, and then dollar volume-weighted across exchanges. We multiply effective and realized spreads as well as price impact by two to be comparable with the quoted spread measure, which captures the full spread. *Tick-constrained* is the percentage of time during the day when the consolidated best bid-ask spread is constrained by the minimum tick increment. Panel B shows distribution of variables at the broker-day and broker-stock-day level. Daily volume represents the total dollar trading volume of a broker on the ASX and Chi-X. Stock-day passive volume is the percentage of volume (number of stocks) in a stock on a day passively traded by a broker (i.e., when a broker does not initiate a trade). Stock-day |order imbalance| is the absolute end-of-day buy-sell order imbalance defined as in Eq. (1).

	NObs	Mean	P10	P25	Median	P75	P90
Panel A: Stock characteristics							
MCap, $AUD mln	93,753	6,459.59	641.96	987.68	1,927.75	4,921.30	12,951.49
Price, $AUD	93,867	8.25	0.18	0.94	1.90	3.82	8.75
Volume, $AUD mln	93,867	24.95	1.31	2.80	7.45	20.13	54.95
Volatility, %	93,867	2.59	1.10	1.52	2.17	3.17	4.51
Quoted spread, bps	93,956	32.29	7.24	13.99	28.13	40.10	57.79
Effective spread, bps	93,857	31.29	6.18	13.03	26.83	38.20	55.22
Realized spread (30 sec), bps	93,857	10.17	-1.24	0.56	5.71	14.93	27.49
Price impact (30 sec), bps	93,857	19.41	5.87	9.72	15.82	24.36	35.17
Tick-constrained, %	93,956	85.30	59.95	80.23	92.41	97.48	99.38
Panel B: Broker characteristics							
# Unique stocks traded per day	40,371	73.79	6.00	17.00	53.00	136.00	171.00
Daily volume, $AUD mln	40,371	126.64	0.69	2.96	15.51	76.80	425.08
Stock-day passive volume, %	2,842,326	47.61	0.00	16.10	48.61	75.99	99.53
Stock-day |order imbalance|, %	2,978,901	58.88	5.77	21.97	61.58	100.00	100.00

Table 2
Characteristics of brokers employing market-making strategies
Panel A of this table summarizes the interim and final outputs of the MM identification procedure described in Section 3.1 We classify a stock-day for a broker as MMing if (i) the order imbalance does not exceed 30%, and (ii) the broker is passive in at least 50% of the executed trading volume. We classify a broker as a potential MM if the median proportion of MMing days for the stocks in her portfolio is at least 20%. The final list of MMs includes brokers with public information confirming their MMing activities and brokers with at least 60% of profitable MMing days. Panel B reports the selected characteristics for the brokers from the final list of MMs. Brokers are divided to HFT MMs and slower incumbent MMs according to the level of their usage of Chi-X (see Section 4.3 for details). Daily volume is the mean (median) daily trading volume defined as in Table 1. Overall/Chi-X market shares compute the mean (median) proportions of the total and passive trading volume (defined as in Table 1) supplied by a MM per stock-day. % MMing days per stock is the mean (median) percentage of days per stock, in which a broker makes markets according to the stock-day MMing criteria (i) and (ii). % MMing stocks per day is the mean (median) percentage of stocks per day, in which a broker makes markets. # MMing stocks per day is the mean (median) number of stocks per day, in which a broker makes markets. # Times inventory crosses zero is the mean (median) number of times a broker's cumulative position in a stock during the MMing day switches between long to short, assuming that a broker starts and ends the day with zero inventory. MMing trade profitability is the mean (median) *%Profitability* from Eq. (3) calculated on MMing stock-days. % profitable days indicates the proportion of MMing days with non-negative profits during the whole sample period (before the HFT MM 1 entry), where the profit is defined as *$Profi*t in Eq. (2).

Panel A: Identification of market-making brokers	
Initial number of brokers	96
Brokers that have MMing stock-days as determined by order imbalance and passive volume	86
Brokers involved in MMing on a regular basis (potential MMs)	12
Final list of MMs	**5**

Panel B: Characteristics of market-making brokers

	HFT MM 1	HFT MM 2	Incumbent MM 1	Incumbent MM 2	Incumbent MM 3
General characteristics					
Daily volume, $AUD mln	97.51	63.50	63.22	110.50	113.92
	(91.75)	(62.70)	(54.90)	(108.17)	(101.89)
Overall/Chi-X market share in	1.27/23.42	2.05/19.35	0.55/1.04	2.29/2.25	1.88/6.37
total trading volume, %	(0.84/21.27)	(1.62/16.00)	(0.32/0.24)	(1.46/0.70)	(1.34/2.43)
Overall/Chi-X market share in	2.25/51.12	4.59/39.04	1.64/0.00	4.97/0.52	5.82/8.44
passive trading volume, %	(0.98/50.79)	(3.06/34.14)	(0.88/0.00)	(2.97/0.00)	(4.91/0.71)
Market-maker characteristics					
% MMing days per stock	52.25	54.09	30.67	32.24	20.42
	(52.93)	(55.12)	(31.58)	(29.18)	(21.46)
% MMing stocks per day	43.95	61.86	28.26	31.35	21.03
	(35.19)	(76.76)	(23.67)	(31.75)	(21.23)
# MMing stocks per day	74.04	67.42	37.33	50.44	33.58
	(55.00)	(59.00)	(24.00)	(53.00)	(34.00)
# Times inventory crosses zero	14.76	10.27	2.07	2.21	2.06
	(7.00)	(7.00)	(2.00)	(1.00)	(1.00)
MMing trade profitability, bps	5.92	5.29	1.15	20.79	18.38
	(4.51)	(3.89)	(3.08)	(16.55)	(14.19)
% profitable days	88.96	83.88	47.89	86.24	71.06
	(–)	(–)	(65.14)	(92.66)	(77.06)

Table 3

Introduction of the new speed technology and profits of slower incumbent MMs

This table reports the results from OLS regressions that analyze the impact of the ASX ITCH introduction on slower incumbent MMs' dollar profits, trade profitability, and proportion of passive trades executed in a tick-constrained environment:

$$Y_{b,s,d} = \alpha + \beta \mathbb{1}(ASX\ ITCH)_d + \boldsymbol{\gamma Controls_{s,d}} + \delta_d + \varepsilon_{b,s,d}.$$

$Y_{b,s,d}$ is one of the following dependent variables for broker *b* in stock *s* on day *d*: *$Profit* defined as in Eq. (2), *%Profitability* defined as in Eq. (3), or *%TickConstrTrades* defined as the proportion of passive trading volume executed when the bid-ask spread is constrained by the minimum tick size. 𝟙(*ASX ITCH*) is the indicator variable that equals one for the period after the ASX ITCH introduction, and zero otherwise. 𝟙(*ASX ITCH*)$^{[5\ months]}$ is defined analogous to 𝟙(*ASX ITCH*), but limits the sample to the five months before and after the ASX ITCH introduction. ***Controls*** is the vector of stock-day control variables: log *Volume*, *Volatility*, *Tick-constrained*, and *Effective spread* defined as in Table 1. We run regressions only on MMing stock-days defined as in Table 2. The main sample period is from January 1, 2011, to February 28, 2013. The inclusion of day fixed effects is indicated at the bottom of the table. T-statistics are reported in parentheses and are derived from double-clustered standard errors by broker and stock. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	$Profit				*%Profitability*				*%TickConstrTrades*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
𝟙(*ASX ITCH*)	-885.094**	-803.188**			-8.600*	-4.517			0.034	0.071***		
	(-2.170)	(-2.172)			(-1.664)	(-1.176)			(0.695)	(3.184)		
𝟙(*ASX ITCH*)$^{[5\ months]}$			-725.376	-761.932			-4.460	-5.858			0.140***	0.013
			(-1.154)	(-1.087)			(-0.339)	(-0.381)			(5.179)	(0.498)
log(*Volume*)		-50.384		-7.177		-4.140***		-4.910***		-0.000		-0.001
		(-0.865)		(-0.246)		(-2.643)		(-3.576)		(-0.030)		(-0.157)
Volatility		-0.159		-0.673		-0.024		-0.023		-0.000**		-0.000*
		(-0.262)		(-0.946)		(-1.215)		(-1.221)		(-2.301)		(-1.853)
Effective spread		1.104		2.490*		0.221***		0.154		0.000***		0.000*
		(1.021)		(1.862)		(3.274)		(1.171)		(3.460)		(1.914)
Tick-constrained		7.185		1.997		0.026		0.050		0.008***		0.008***
		(1.335)		(0.300)		(0.351)		(0.333)		(70.334)		(38.891)
Day FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.013	0.014	0.015	0.015	0.013	0.019	0.012	0.019	0.053	0.635	0.033	0.657
NObs	72,281	72,266	28,189	28,191	72,281	72,266	28,189	28,191	72,277	72,266	28,195	28,191

Table 4

Introduction of the new speed technology and profits of HFT MMs

This table reports the results from OLS regressions that analyze the impact of the ASX ITCH introduction on HFT MMs' dollar profits and trade profitability:

$$Y_{b,s,d} = \alpha + \beta \mathbb{1}(ASX\ ITCH)_d + \boldsymbol{\gamma Controls_{s,d}} + \delta_d + \varepsilon_{b,s,d}.$$

$Y_{b,s,d}$, $\mathbb{1}(ASX\ ITCH)$, $\mathbb{1}(ASX\ ITCH)^{[5\ months]}$, and ***Controls*** are defined as in Table 3. We run regressions only on MMing stock-days defined as in Table 2. The main sample period is from January 1, 2011, to February 28, 2013. The inclusion of day fixed effects is indicated at the bottom of the table. T-statistics are reported in parentheses and are derived from double-clustered standard errors by broker and stock. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	$Profit				*%Profitability*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}(ASX\ ITCH)$	171.267***	459.956***			7.615***	1.614		
	(3.069)	(4.867)			(7.967)	(1.106)		
$\mathbb{1}(ASX\ ITCH)^{[5\ months]}$			202.254	209.606*			-7.326	-12.569
			(1.493)	(1.913)			(-0.922)	(-1.611)
log(*Volume*)		91.181***		84.296***		-1.314***		-1.450*
		(11.728)		(6.368)		(-2.590)		(-1.843)
Volatility		-0.337*		-0.422*		-0.027***		-0.028***
		(-1.713)		(-1.670)		(-4.325)		(-3.891)
Effective spread		1.930		1.767		0.165***		0.148***
		(1.310)		(1.110)		(3.116)		(3.229)
Tick-constrained		2.237***		1.466***		0.018		0.018
		(4.118)		(3.284)		(0.543)		(0.763)
Day FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.025	0.059	0.020	0.059	0.012	0.046	0.011	0.042
NObs	48,851	48,841	29,269	29,264	48,851	48,841	29,269	29,264

Table 5
Introduction of the new speed technology and market-making profits, placebo test
This table reports the results from the placebo test of the ASX ITCH impact on profits and trade profitability from market making. Specifically, we run the same OLS regressions as in Table 4 for quasi market-making brokers, which are not expected to earn money from liquidity provision. These brokers are identified as potential MMs, but do not qualify to the final list of MMs due to insufficient number of profitable MMing days (see Section 4.2 and Table 2 for details). We run regressions only on MMing stock-days defined as in Table 2. The main sample period is from January 1, 2011, to February 28, 2013. The inclusion of day fixed effects is indicated at the bottom of the table. T-statistics are reported in parentheses and are derived from double-clustered standard errors by broker and stock. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	$Profit				*%Profitability*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
𝟙(*ASX ITCH*)	1,168.218	-42.237			-0.185	-3.798		
	(0.878)	(-0.024)			(-0.048)	(-0.837)		
𝟙(*ASX ITCH*)$^{[5\ months]}$			1,577.100	2,427.004			1.968	2.035
			(0.096)	(0.148)			(0.089)	(0.090)
log(*Volume*)		658.202		-291.817		1.516		0.555
		(0.501)		(-0.455)		(0.846)		(0.728)
Volatility		-1.816		3.627		0.005		0.032
		(-0.198)		(0.348)		(0.234)		(1.200)
Effective spread		110.747		6.137		0.296		-0.012
		(0.663)		(0.141)		(0.954)		(-0.148)
Tick-constrained		-82.312		-71.280		-0.170		-0.014
		(-0.738)		(-1.272)		(-1.010)		(-0.349)
Day FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.004	0.004	0.003	0.003	0.006	0.009	0.007	0.011
NObs	217,024	216,980	83,590	83,578	217,024	216,980	83,590	83,578

Table 6
Profitability and adverse selection borne by slower incumbent MMs

This table reports the results from OLS regressions that analyze the impact of the ASX ITCH introduction on realized spread and price impact shortly after slower incumbent MMs' passive trades:

$$Y_{b,s,d} = \alpha + \beta\mathbb{1}(ASX\ ITCH)_d + \boldsymbol{\gamma Controls_{s,d}} + \delta_d + \varepsilon_{b,s,d}.$$

$Y_{b,s,d}$ is either *Realized spread* (30 sec) or *Price impact* (30 sec) defined as in Table 1 over passive trades executed by incumbent MMing broker *b* in stock *s* on day *d*. $\mathbb{1}$(*ASX ITCH*) and $\mathbb{1}$(*ASX ITCH*)$^{[5\ \text{months}]}$ are defined as in Table 3. ***Controls*** include previous-month average daily log *Volume* and *Volatility* as well as *Price* at the end of the previous month (all defined as in Table 1). Panel A reports the regression results for passive trades executed by slower incumbent MMs when the bid-ask spread is constrained by the minimum tick increment. Panel B report the results for passive trades executed when the bid-ask spread is *not* constrained by the minimum tick increment. We run regressions only on MMing stock-days defined as in Table 2. The main sample period is from January 1, 2011, to February 28, 2013. The inclusion of day fixed effects is indicated at the bottom of the table. T-statistics are reported in parentheses and are derived from double-clustered standard errors by broker and stock. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Tick-constrained environment

	Realized spread (30 sec)				*Price impact* (30 sec)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$(*ASX ITCH*)	3.935	1.814			-0.783	2.775		
	(0.516)	(0.398)			(-0.172)	(0.836)		
$\mathbb{1}$(*ASX ITCH*)$^{[5\ months]}$			1.147	0.073			15.900**	17.025**
			(0.478)	(0.033)			(7.421)	(5.308)
log(Volume)		-0.882**		-1.589***		-1.061		-0.814
		(-2.112)		(-4.293)		(-1.448)		(-0.932)
Volatility		0.012		0.011		0.080***		0.086***
		(1.233)		(1.196)		(8.006)		(6.769)
Price		-0.220***		-0.225**		-0.400***		-0.437***
		(-2.612)		(-2.057)		(-3.870)		(-3.968)
Day FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.019	0.055	0.017	0.075	0.022	0.203	0.021	0.236
NObs	69,408	66,997	26,899	26,791	69,408	66,997	26,899	26,791

Panel B: Tick-unconstrained environment

	Realized spread (30 sec)				*Price impact* (30 sec)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$(*ASX ITCH*)	-19.119**	-9.997***			19.456***	15.292***		
	(-2.266)	(-4.133)			(4.853)	(3.458)		
$\mathbb{1}$(*ASX ITCH*)$^{[5\ months]}$			10.161	10.509			4.843	5.836
			(0.599)	(0.732)			(0.447)	(0.479)
log(Volume)		-1.827***		-2.046***		-2.586***		-2.447***
		(-2.675)		(-2.679)		(-5.685)		(-4.788)
Volatility		0.084***		0.090***		0.057***		0.060***
		(4.232)		(4.061)		(7.595)		(6.765)
Price		-0.570***		-0.671***		-0.144**		-0.150**
		(-3.162)		(-2.953)		(-2.257)		(-2.467)
Day FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.021	0.123	0.018	0.153	0.020	0.065	0.016	0.071
NObs	41,035	39,662	16,139	16,088	41,035	39,662	16,139	16,088

Table 7
Profitability and adverse selection borne by HFT MMs
This table reports the results from OLS regressions that analyze the impact of the ASX ITCH introduction on realized spread and price impact shortly after HFT MMs' passive trades:

$$Y_{b,s,d} = \alpha + \beta \mathbb{1}(ASX\ ITCH)_d + \boldsymbol{\gamma Controls_{s,d}} + \delta_d + \varepsilon_{b,s,d}.$$

All variables defined as in Table 6. Panel A reports the regression results for passive trades executed by HFT MMs when the bid-ask spread is constrained by the minimum tick increment. Panel B report the results for passive trades executed when the bid-ask spread is *not* constrained by the minimum tick increment. We run regressions only on MMing stock-days defined as in Table 2. The main sample period is from June 10, 2011, to February 28, 2013. The inclusion of day fixed effects is indicated at the bottom of the table. T-statistics are reported in parentheses and are derived from double-clustered standard errors by broker and stock. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Tick-constrained environment

	Realized spread (30 sec)				*Price impact* (30 sec)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
𝟙(ASX ITCH)	19.450***	-9.318***			8.254***	-14.941***		
	(12.625)	(-3.140)			(8.019)	(-3.154)		
𝟙(ASX ITCH)[5 months]			6.316**	-4.815***			16.846***	9.765***
			(2.459)	(-3.591)			(2.973)	(3.949)
log(Volume)		-1.238**		-1.596**		-2.183**		-2.047*
		(-2.373)		(-2.259)		(-2.175)		(-1.886)
Volatility		0.034***		0.026*		0.066***		0.064***
		(3.407)		(1.688)		(5.229)		(4.357)
Price		-0.531***		-0.602***		-0.153***		-0.251***
		(-6.957)		(-5.038)		(-3.754)		(-3.341)
Day FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.057	0.132	0.061	0.142	0.062	0.173	0.065	0.181
NObs	47,355	47,216	28,470	28,372	47,355	47,216	28,470	28,372

Panel B: Tick-unconstrained environment

	Realized spread (30 sec)				*Price impact* (30 sec)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
𝟙(ASX ITCH)	26.072***	-15.918***			10.390***	-11.451***		
	(4.310)	(-3.885)			(2.620)	(-2.911)		
𝟙(ASX ITCH)[5 months]			-9.883	-22.963***			15.817*	8.313***
			(-1.634)	(-9.419)			(1.837)	(4.050)
log(Volume)		-1.653***		-1.988***		-3.790**		-3.878*
		(-2.672)		(-2.613)		(-2.344)		(-1.650)
Volatility		0.078***		0.079***		0.049***		0.060***
		(3.841)		(6.155)		(3.911)		(3.799)
Price		-0.749***		-0.858***		-0.026		-0.099**
		(-4.744)		(-3.643)		(-0.756)		(-2.377)
Day FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.043	0.146	0.033	0.137	0.022	0.062	0.018	0.063
NObs	24,542	24,483	14,551	14,515	24,542	24,483	14,551	14,515

Table 8
Fragmentation and profits from market making
This table reports the results from OLS regressions that analyze the impact of fragmentation on MMs' dollar profits and trade profitability:

$$Y_{b,s,d} = \alpha + \beta \, Chi\text{-}X \ market \ share_{s,d} + \boldsymbol{\gamma Controls_{s,d}} + \delta_d + \varepsilon_{b,s,d}.$$

$Y_{b,s,d}$ and ***Controls*** are defined as in Table 3. *Chi-X market share*$_{s,d}$ is the percentage market share of Chi-X in the total dollar trading volume across exchanges for stock *s* on day *d*. We run regressions only on MMing stock-days defined as in Table 2. The main sample period is from January 1, 2011, to February 28, 2013. The inclusion of day fixed effects is indicated at the bottom of the table. T-statistics are reported in parentheses and are derived from double-clustered standard errors by broker and stock. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	HFT MMs				Incumbent MMs			
	$Profit		*%Profitability*		*$Profit*		*%Profitability*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Chi-X market share	6.989***	3.845***	0.196***	0.103**	13.286	10.167	0.247	0.126
	(8.383)	(3.258)	(2.678)	(2.120)	(1.462)	(1.221)	(1.082)	(0.574)
log(*Volume*)		90.103***		-1.343**		-36.587*		-5.164***
		(7.565)		(-2.533)		(-1.706)		(-3.484)
Volatility		-0.328*		-0.027***		-0.405		-0.017
		(-1.652)		(-4.337)		(-0.659)		(-0.914)
Effective spread		1.889		0.164***		2.235		0.174
		(1.263)		(3.024)		(1.283)		(1.627)
Tick-constrained		1.981***		0.011		1.636		0.010
		(3.323)		(0.357)		(0.273)		(0.107)
Day FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.024	0.055	0.013	0.046	0.017	0.017	0.013	0.018
NObs	48,790	48,790	48,790	48,790	36,719	36,719	36,719	36,719

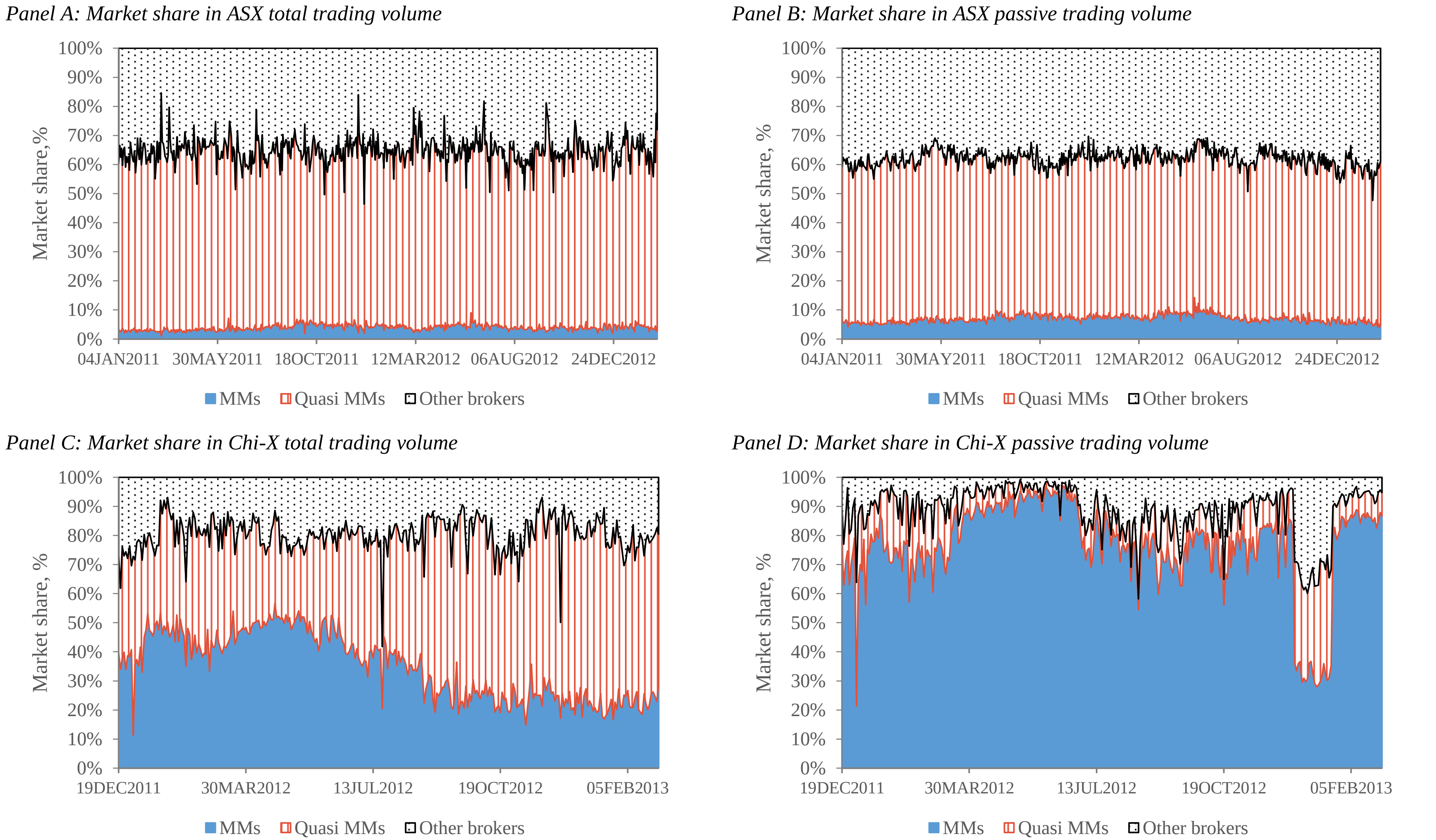
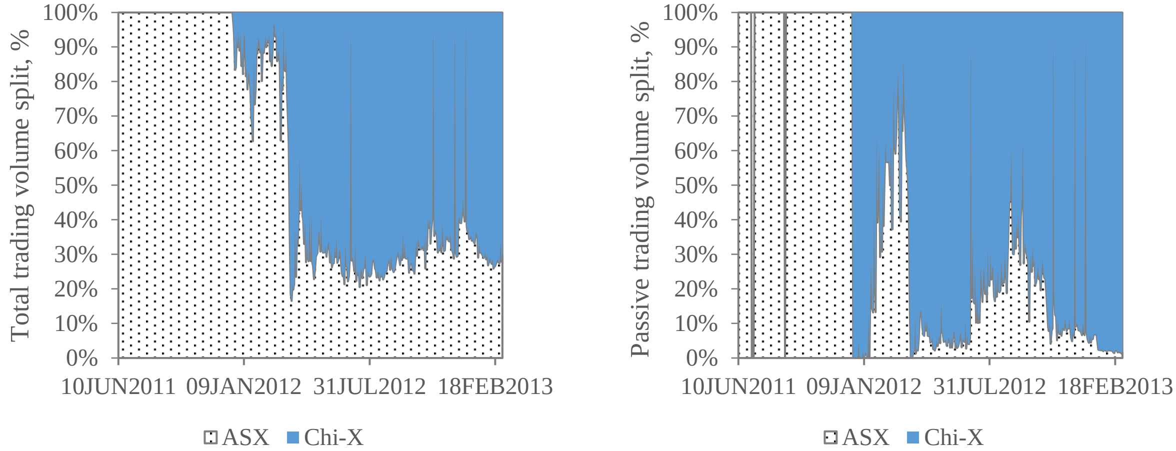


Fig. 1. **Market shares of MMs in total and passive trading volumes on the ASX and Chi-X.** This figure plots the time series evolution of market shares in total and passive trading volumes of different brokers on the ASX and Chi-X from January 1, 2011, to February 28, 2013. The blue solid area represents the overall market share of five MMs from the final list (see Table 2). The red striped area represents the overall market share of seven quasi MMing brokers (investment banks), which are identified as potential MMs but do not qualify to the final list of MMs due to insufficient number of profitable MMing days (see Section 4.2 and Table 2). The black dotted area represents the overall market share of the leftover 84 brokers.

Panel A: HFT MM 1



Panel B: HFT MM 2

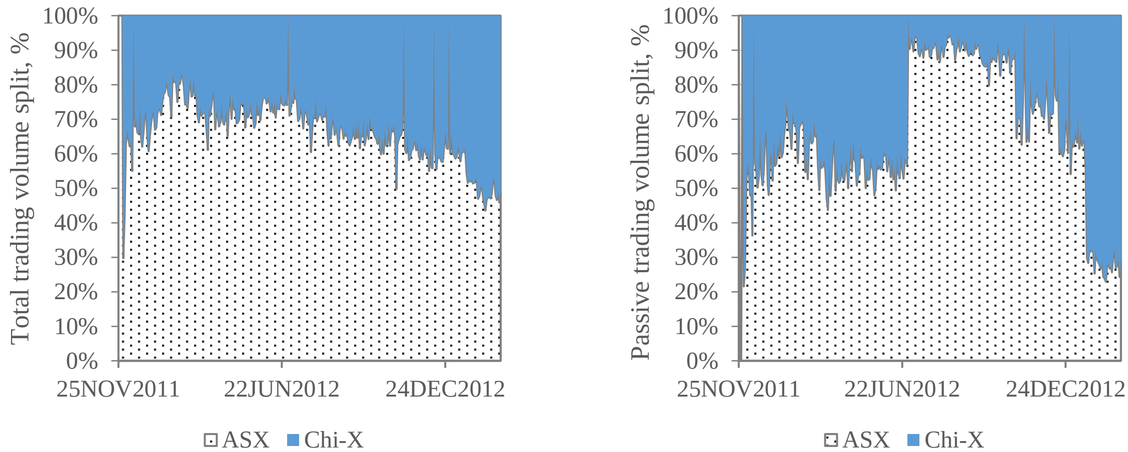
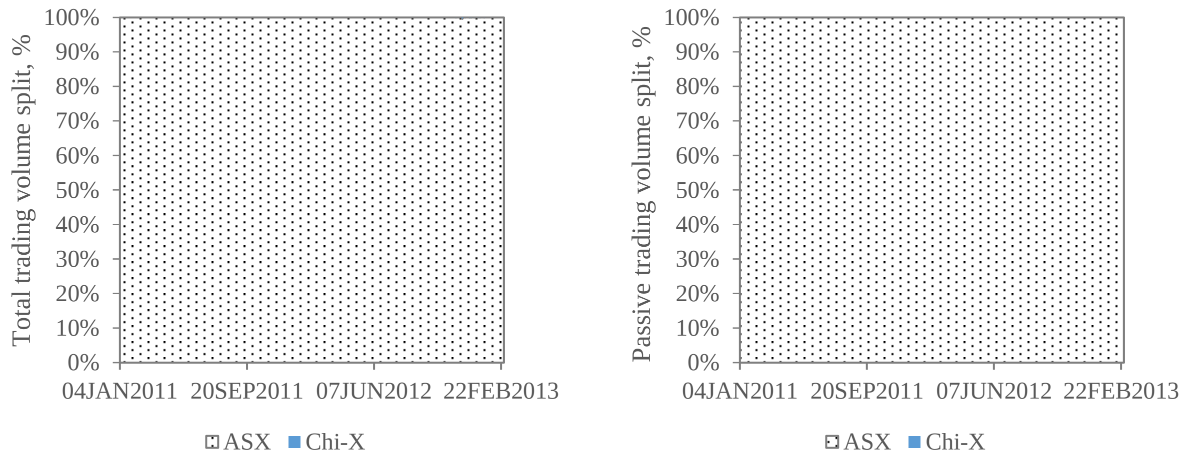
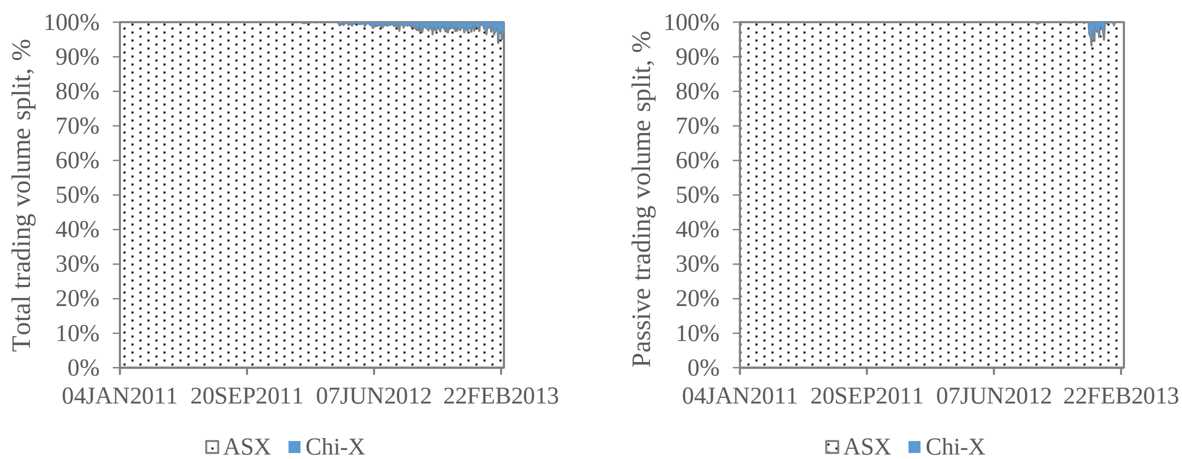


Fig. 2. **Exchange choice by HFT MMs.** This figure plots the proportion of total and passive dollar trading volume executed by HFT MMs on the ASX (black dotted area) and Chi-X (blue solid area). The sample period starts from the time a HFT MM first appears in the data until the end of the sample period (February 28, 2013).

Panel A: Incumbent MM 1



Panel B: Incumbent MM 2



Panel C: Incumbent MM 3

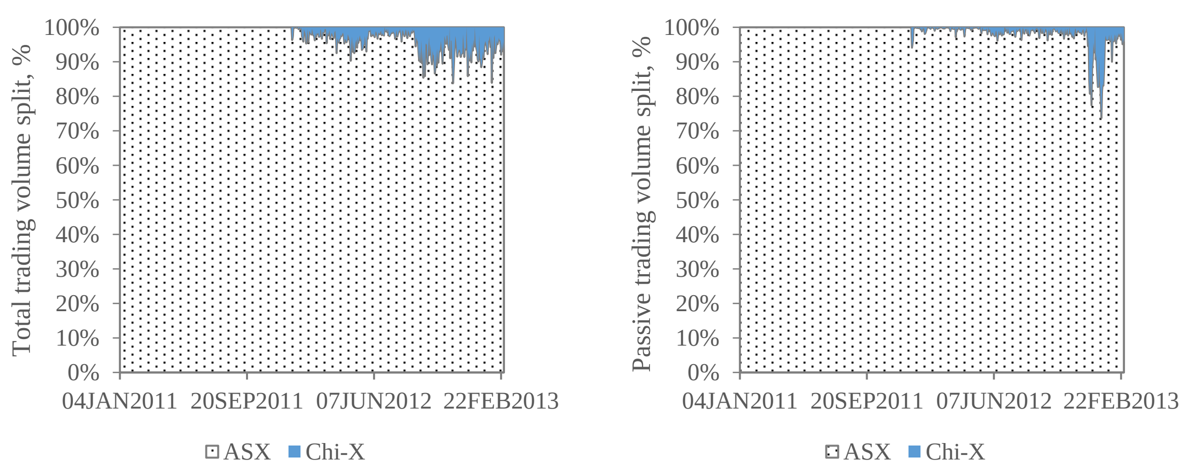


Fig. 3. **Exchange choice by incumbent MMs.** This figure plots the proportion of total and passive dollar trading volume executed by incumbent MMs on the ASX (black dotted area) and Chi-X (blue solid area). The sample period is from January 1, 2011, to February 28, 2013.