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Broker Colocation and the Execution Costs of Customer and Proprietary Orders

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Broker colocation and the execution costs of customer and proprietary orders*

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Abstract

Colocation services offered by stock exchanges enable market participants to achieve execution costs for large orders that are substantially lower and less sensitive to transacting against high-frequency traders. However, these benefits manifest only for orders executed on the colocated brokers' own behalf, whereas customers' order execution costs are substantially higher. Analyses of individual order executions indicate that customer orders originating from colocated brokers are less actively monitored and achieve inferior execution quality. This suggests that brokers do not make effective use of their technology, possibly due to agency frictions or poor algorithm selection and parameter choice by customers.

Keywords: Execution Cost, Institutional Investor, Broker, High-Frequency Trading, Colocation

JEL classification: G10, G14, G15

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1 Introduction

> "[B]rokers and other industry players are learning from [...] HFT strategies and in turn offering tools to their clients[...] that take advantage of the same sophisticated technology and logic. We're all high frequency traders now."
>
> Credit Suisse Whitepaper (Avramovic et al., 2017)

Equity market participants invest heavily in the speed of market access by employing cutting-edge hardware, relying on real-time market data feeds, and subscribing to exchanges' colocation facilities in order to place their servers within the exchanges' datacenters in close proximity to the matching engine. While the academic literature has explored the role of trading speed in the context of high-frequency trading (HFT), the impact of the speed of institutional investors and broker-dealers on their trading outcomes remains unexplored.[1]

We investigate how the execution costs for large orders traded in a proprietary or agency capacity are affected by the use of exchanges' colocation facilities. Trades executed by colocated exchange members in a proprietary capacity achieve about 6 basis points (henceforth bps) lower execution costs compared to similar orders executed without colocation. However, agency orders do not benefit to any extent from brokers' colocation. After controlling for commonly used predictors of execution costs (market conditions, order characteristics, and trading strategy), agency orders executed by colocated brokers experience higher costs as compared to proprietary ones. The difference in execution costs between the two capacities is almost 5 bps across all exchange members and 9 bps within the subsample of broker-dealers who execute orders in both agency and proprietary

[1] For the remainder of the paper, we use the terms exchange member, broker, and broker-dealer interchangeably.

capacities.

The magnitude of these differences in execution costs are economically large compared to average quoted spreads of 9 bps for the largest tercile of stocks, which account for the majority of trading volume in our sample. A back-of-the envelope calculation further suggests that the incremental costs incurred by agency compared to proprietary orders executed by colocated brokers are economically sizable at more than 300 million euros annually.[2]

We also find that the execution costs of brokers using colocation for proprietary orders are less affected by the extent to which they interact with the flow of HFT firms. Trading against HFT firms is generally associated with higher execution costs, though this is driven by transactions against HFTs acting as aggressive counterparties, whereas the opposite holds for passive, liquidity providing HFT counterparties. The magnitude of these effects is around 3.5 bps and −3.0 bps for a 10 percentage point increase in the share of the aggressive and passive HFT as counterparties to the large order, respectively. Conditional on exchange members being colocated, the effect of aggressive HFT on execution costs of proprietary orders is reduced by more than half but remains positive, whereas the conditional effect of passive HFT is smaller in magnitude but remains negative. These results indicate that access to speed-enhancing facilities potentially allows large traders to reduce the sensitivity of execution outcomes to the nature and technological sophistication of their counterparties.

There are several potential explanations for the fact that, while colocation allows broker-dealers to obtain better execution outcomes for large orders, these benefits are largely limited to their proprietary orders. To the extent that broker-dealers provide the

[2]This number is obtained by multiplying the average trade size by the number of colocated agency trades, the difference in execution costs, the ratio of the length of a year relative to our sample period, and the ratio of the number of stocks relative to the number contained in our sample.

same algorithmic execution strategies to their customers that they use when trading in a principal capacity, the differences in execution outcomes indicate the presence of inefficiencies in the choice of algorithm and/or the parameters governing such algorithms employed by the customers. The use of algorithms developed by third party providers or by large buy-side investors in-house (see, for example, Frazzini et al., 2018) – possibly inferior to algorithms provided by brokers – and then deployed using an exchange member's direct electronic access infrastructure may also help explain the results. Finally, an alternative or supplemental explanation of our results may be that the choice of execution algorithms brokers make available to customers is different to those used for their proprietary trades.

To better understand the channels behind our main results, we investigate the order submission behavior and the execution quality at the level of the child orders that constitute the large parent orders. In an algorithmic trading setup, one major characteristic of an algorithm is its' ability to monitor orders actively with low latency. We find that, compared to colocated agency orders, the proprietary counterparts on average have higher order-to-trade ratios. This suggests that the algorithms used to execute proprietary orders monitor the limit order book more actively – possibly in event time as opposed to calendar time (Bacidore, 2020). We furthermore find a higher degree of periodicity in colocated agency as compared to proprietary orders, which is consistent with a more prevalent use of timer-based algorithms for agency trades. Brugler (2015) and Sağlam (2020) also provide evidence of calendar-time periodicity in trading activity, which in Sağlam (2020) is associated with poor execution quality. Finally, the individual child order executions of proprietary orders experience better execution quality when measured in terms of effective spreads and price impacts in comparison to observationally similar agency orders. These results altogether suggest that the quality of child order executions for agency orders is inferior compared to that of proprietary orders.

It is unclear whether our results constitute evidence for a formal violation of brokers' best execution obligations for at least two reasons. First, in contrast to the US, brokers in the EU have significant flexibility when defining their best execution policies. Second, to the extent customers make poor choices when using the algorithms provided by the brokers, brokers are not in violation of any obligations. However, if the clients make these poor execution decisions, brokers could better educate their customers to eliminate such inefficiencies. Regardless of whether our results are interpreted as consistent with best execution, our approach of benchmarking client execution outcomes against brokers' own orders may be useful for brokers to demonstrate, and regulators to verify, best execution.

Our results are based on a pan-European equity market dataset made available by the European Securities and Markets Authority (ESMA). The data contains exchange message-level information including masked identifiers of exchange members whose activity can be tracked across stocks and exchanges. We aggregate individual order executions to 11,724 parent orders based on unidirectional order flow of non-HFT exchange members and examine the determinants of execution costs for these parent orders using a doubly robust estimator combining panel regressions with inverse probability weights. Our results also hold for simple fixed effects models and are robust to including exchange fees in the execution costs.

A potential concern in our analysis is that our regression design does not fully control for the differences in trading motives or investment styles across agency and proprietary orders. While investors' trading motives are not directly observable in our dataset, our choice of control variables and fixed effects indirectly controls for trading motives and differences in execution strategy originating from heterogeneous trading motives. Specifically, our regressions are estimated within stock-day and also control, *inter alia,* for the time of day the execution begins. Additionally, we control for the volatility and short-term return of the stock immediately before trading, the size of the parent order, its total time of execution, its number of executed child orders, the proportion of liquidity-consuming child orders, the total trading volume in the stock, the proportion of trading executed away from the primary exchange, and the information content of the order. Thus, we consider it unlikely that unobserved trading motives would affect execution costs to any substantial extent.

Our paper contributes to the literature on brokers' order handling practices and their impact on institutional execution costs. Barbon et al. (2019) find evidence that brokers leak information on institutional trades to other customers, which leads to increased execution costs for those trades. Conrad et al. (2001) show that institutional investors' use of soft dollar brokers, i.e., those providing sell-side research in exchange for executing trades, is associated with higher transaction costs. Anand et al. (2011), while mainly concerned with the performance of trading desks of institutional investors, find that broker execution performance is persistent and related to trading commissions. Anand et al. (2021) show that institutional execution costs are higher for brokers sending a large share of orders to affiliated alternative trading systems. Battalio et al. (2018) study the effect of routing orders to off-exchange high-frequency liquidity providers and find that such behavior leads to higher execution costs on institutional orders. However, apart from trading venue choices, prior literature provides little evidence on how and why execution costs differ across brokers. Our paper fills this gap by focusing on the role of technology, specifically colocation, as a differentiating factor that enables the effective use of sophisticated algorithms.

Our paper also contributes to the literature on speed dispersion. This literature finds that the effect of faster HFTs on slower non-HFTs depends on whether the former use their speed advantage to provide liquidity (as in Ait-Sahalia and Saglam, 2017; Brogaard et al., 2015) or to engage in arbitrage or back-running (as in Foucault et al., 2016; Shkilko and Sokolov, 2020). Our paper, while obtaining results consistent with both views, shows that broker-dealers' investment in enhancing their speed of market access can reduce the sensitivity of execution costs to trading against HFTs.

We also contribute to the literature studying the effects of HFT on the trading activity and associated costs of institutional investors.[3] Yang and Zhu (2020) extend the two-period Kyle (1985) model by including a "back-runner" – a trader who infers the fundamental information by observing the order flow – alongside the informed trader. The former's presence leads to less aggressive trading by the informed trader, thereby delaying price discovery.[4] Korajczyk and Murphy (2019) show that, in the Canadian equity market, the presence of HFT firms engaging in market-making activity leads to higher transaction costs for large institutional trades. Van Kervel and Menkveld (2019) find that, in the Swedish equity market, HFTs provide liquidity early-on during institutional trades but later turn to trade in the same direction. Sağlam (2020) observes that

[3]More broadly, prior research shows that HFT has a positive or, at least, benign effect on common measures of market liquidity, such as bid-ask spreads, and price efficiency, such as variance ratios (e.g. Hasbrouck and Saar, 2013; Menkveld, 2013; Brogaard, Hendershott, and Riordan, 2014). See Menkveld (2016) for a survey.

[4]In addition to HFTs affecting the profitability of investors' trading strategies and price discovery in the market, several studies have shown that rent seeking behaviour by HFTs negatively affects investors' information acquisition decision. Baldauf and Mollner (2020) model a fragmented market in which HFTs can both demand and supply liquidity. HFTs anticipate other participants' order flow and, as they become faster, information acquisition decreases. Dugast and Foucault (2018) show that the existence of inexpensive unprocessed but imprecise information can lead market participants to reduce their demand for processed and more accurate information, leading to a decrease in price informativeness. Weller (2017), in a study of algorithmic trading – a superset of HFT – in the U.S. equity market, and Gider, Schmickler, and Westheide (2021), in an international study on HFT, find evidence consistent with this idea.

execution algorithms such as the Volume-Weighted Average Price (VWAP) can lead to predictable patterns in order flow that can be picked up by HFTs. Putniņš and Barbara (2016) find that, in the Australian equity market, the effects of HFT firms on institutional transaction costs differ in the cross-section of HFT firms, with some affecting them positively and others negatively. Tong (2015), in a study of the U.S. equity market, obtains evidence that institutional execution costs increase with the amount of HFT. She also observes that this effect is alleviated for some institutional investors with high levels of trading skills, as measured by historical transaction costs, though her data do not allow her to explore the determinants of institutional trading skills. Chen and Garriott (2020) find that HFT in the Canadian bond futures market leads to lower institutional execution costs for relatively small parent orders. Finally, Brogaard, Hendershott, Hunt, and Ysusi (2014) do not find any causal effect of HFT on institutional transaction costs on the London Stock Exchange. Our paper contributes to this literature by establishing differential effects of trading against aggressive and passive HFT orders, and by showing that brokers can reduce these effects through their own trading speed.

The remainder of the paper is structured as follows. Section 2 presents the data and discusses the variables used. In section 3, we discuss the measurement and potential determinants of execution costs. The estimation approach is detailed in section 4. Section 5 contains descriptive statistics at the levels of exchange members and parent orders. In section 6, we present the parent order level results. Section 7 contains analyses of order submissions and the execution quality of child orders. Section 8 concludes.

2 Data

Our analysis is based on the proprietary high-frequency database of the European Securities and Markets Authority (ESMA). This database was designed by the regulator to study HFT activity in fragmented equity markets in the EU. The original sample comprises 98 stocks from nine countries – Belgium, Germany, Spain, France, Ireland, Italy, the Netherlands, Portugal and the United Kingdom – that were members of the EU at the time. Dependent on the size of the national markets, between 5 and 16 stocks are chosen for each country via a stratified sampling approach to ensure it is representative of the EU market with respect to market value, trading volume, and level of fragmentation. The database includes all order messages and trades for each stock from the respective primary market and the three main lit multilateral trading facilities (MTFs) – Chi-X, BATS, and Turquoise – for the 22 trading days in May 2013. The data allow us to track individual exchange members' activity across all trading venues. Bouveret et al. (2014) provide detailed information on the sample selection approach and the database construction, as well as a first analysis of HFT activity based on the data.[5]

2.1 Member Categorization, Trading Capacity, and Colocation

While individual members' identities remain unknown to us, ESMA groups them into three categories: HFTs, Investment Banks, and Others. Previous studies identify HFT firms either based on their primary business model or on measures of trading and quoting activity such as order-to-trade ratios or order lifetimes. Bouveret et al. (2014) compare

[5]The dataset, however, excludes trading activity in off-exchange venues such as dark pools, systematic internalizers, and the over-the-counter market. To the best of our knowledge, statistics on institutional usage of such venues in the EU are unavailable. However, Beason and Wahal (2020) observe that, for a single firm providing algorithmic execution services in the US, over 77% of child orders are routed to lit venues.

these two identification approaches and find that the former provides a conservative estimate by only including proprietary trading firms and excluding HFT activity originating at investment banks. It also prevents the erroneous classification of sophisticated traders employing low latency infrastructure as HFTs, even though their business model substantially differs from that of HFTs. For example, Avramovic et al. (2017) argue that the quoting and trading behavior (speed of response to market events, order-to-trade ratios, etc.) of large technologically sophisticated broker-dealers may resemble that of HFTs, even though the size and holding period of their positions are vastly different. We hence rely on the HFT flag based on the former approach, which categorizes 20 exchange members as HFTs, 18 of which serve as counterparties to the institutional trades identified below.

Trading activity by individual exchange members is further split by capacity into trading on behalf of customers (agency) and trading on the firm's own account (proprietary). We rely on this flag to identify differences in execution quality between institutional trades executed by exchange members on behalf of their clients and on a proprietary basis. This flag is generated by ESMA based on the reporting of this information by trading venues.[6]

Finally, the database also contains a binary variable indicating whether members use the colocation service offered by the different trading venues, i.e. whether members have located their equipment within the venues' data centers. Colocation, combined with a subscription to the venues' low latency market data feeds, allows members to minimize the round-trip latency between their servers and the venues' matching engines.[7] We

[6]While Bouveret et al. (2014) report inconsistencies in the reporting of this information by the venues, those issues were subsequently fixed. This has been confirmed to us by ESMA. Furthermore, the reporting of riskless principal orders by some brokers as proprietary may introduce some noise in our results. However, we do not expect the magnitude of this noise to be substantial or to bias our results.

[7]We acknowledge that colocation, potentially, could also be used as a cost-efficient alternative for

distinguish colocation on the primary markets from that on the MTFs. While we are able to directly observe whether an individual exchange member is colocated on the primary listing venue, we proxy for colocation on the MTFs based on whether the member is colocated on Turquoise. This is because we cannot directly observe such a flag for BATS Chi-X. We also exclude the 12 Spanish stocks from our sample as the colocation flag for the Spanish stock exchange is missing.

2.2 Identification of Institutional Orders

Large institutional parent orders are typically split into multiple smaller child orders and then executed over time and across venues. While our dataset allows us to track the message traffic (order submissions, cancellations, and transactions) of individual exchange members, we do not have information on the parent order's size. Korajczyk and Murphy (2019) and Van Kervel and Menkveld (2019) solve this problem by stitching together a string of child order executions.

Korajczyk and Murphy (2019) define an institutional parent order as an uninterrupted sequence of one or more trades on the same side by the same exchange member if the total volume of those trades is at least CAD 100,000.[8] Van Kervel and Menkveld (2019), on the other hand, start by first lumping together all executions on a given stock-day and then applying a directionality (the difference of buy and sell volume relative to total volume) cutoff of 90%. Both combine parent orders across days if there is a child order executed during both the last and first 30 minutes of two consecutive days. We employ

foreign firms to establishing an office in a country. If that were true for a subset of the exchange members in our sample, it would attenuate our results related to the differences in execution costs between orders originating from colocated versus non-colocated members. Furthermore, EU's single passport rights allows non-EU firms to trade across the European single market by using an office in one EU-member country, thus eliminating the need to colocate on multiple venues. However, the most active exchange members in our sample are in fact colocated across multiple venues.

[8] Korajczyk and Murphy (2019) use this cutoff based on the distribution of institutional order size in the US market as reported by Chan and Lakonishok (1995) and Cready et al. (2014).

the methodology of Korajczyk and Murphy (2019) to identify parent orders by applying an order size cutoff of €100,000.[9] Following Putniņš and Barbara (2016), we further require that a parent order is worked in the market for at least two hours. For our final sample of institutional orders, we additionally require an exchange member to have at least ten parent orders across all stocks. We use the capacity flag to further classify orders into those executed on behalf of a customer (agency execution) or on the exchange member's own account (proprietary execution) and construct parent orders separately for each capacity such that a single parent order consists of agency or proprietary child orders only.

3 Measuring and Explaining Execution Costs

In this section, we explain how we measure the execution costs of large orders. We also describe the commonly-used determinants of execution costs that act as controls in our main analysis.

3.1 Measuring Parent Order Level Execution Costs

Perold (1988) defines implementation shortfall as the cost of implementing investment decisions and further decomposes it into execution costs and opportunity costs. The former relates to transactions actually executed while accounting for the fact that individual child orders may execute at different prices. Implicitly, the execution cost component includes instantaneous transaction costs such as the bid-ask spread as well as the price impact associated with the actions taken by other market participants upon detecting

[9] All parent orders identified using our approach originate from non-HFT members. This is unsurprising considering HFT firms generate their profits, not by acquiring large positions, but by rapidly turning over their positions at high-frequencies, while providing liquidity and/or exploiting short-term informational asymmetries.

the presence of a large institution in the market as in Brunnermeier and Pedersen (2005), Ait-Sahalia and Saglam (2017), and Yang and Zhu (2020). The latter component relates to transactions that cannot be executed. As in most other studies of institutional transaction costs (Keim and Madhavan, 1997; Korajczyk and Murphy, 2019; Van Kervel and Menkveld, 2019), we ignore the opportunity cost of non-execution as we cannot observe the initially planned parent order size.

For parent order k executed by exchange member i in stock s on day t, the execution cost is defined as

$$\text{Execution Cost}_{istk} = \left(\frac{\text{VWAP}_{istk}}{P^0_{istk}} - 1\right) \times Q_{istk} \tag{1}$$

where VWAP is the value-weighted average price of all child order executions, $Q \in \{-1, 1\}$ is the sign of the order which equals 1 (-1) for buy (sell) orders, and P^0 is the benchmark price. The quote midpoint immediately before the execution of the first child order serves as the benchmark price. We express the execution cost in basis points.

3.2 Determinants of Institutional Execution Costs

Our objective is to evaluate how brokers' use of colocation services affects the execution costs of their parent orders, and whether these effects differ for the brokers' proprietary versus agency executions. The use of exchanges' colocation facilities potentially allows exchange members to get better execution by strategically choosing when to supply and consume liquidity, better managing adverse selection costs, and reacting to changes in market conditions at high speeds. We construct a binary variable for each broker-stock combination based on whether the broker is colocated on any of the markets where the stock trades. A second binary flag associated with each message allows us to identify the capacity (agency or proprietary) in which the orders are submitted.

We control for several factors expected to affect institutional execution costs (see e.g. Chan and Lakonishok, 1997; Keim and Madhavan, 1997; Jones and Lipson, 1999, 2001). Keim and Madhavan (1997, 1998) argue that trading costs are driven by trade difficulty, which they proxy for using trade size, stocks' market capitalization, trader's investment style and other factors. We divide the previously established determinants of execution costs into three broad categories: order characteristics, market conditions, and execution strategy.

Several studies (Keim and Madhavan, 1997; Chan and Lakonishok, 1997; Jones and Lipson, 1999) find that institutional trading costs are higher for larger orders as counterparties require larger price concessions to take the other side of the trade. This is because displayed liquidity, even for the most actively traded stocks, is finite and may not fully absorb a large trade. Investors also perceive traders executing large quantities as better informed (Easley and O'Hara, 1987). To capture these effects, we include the parent order size as a control variable. Furthermore, Chan and Lakonishok (1995) and Engle et al. (2012) argue that trade size should be compared with the stock's typical trading volume when measuring execution costs. Higher overall volume in the market potentially allows the institution to better hide its trading intentions (Kyle, 1985). Hence, we also control for the total volume of all other executed orders across the primary market and the 3 MTFs in our sample during the execution of the parent order.

Previous studies (see for example Chan and Lakonishok, 1993; Saar, 2001; Jones and Lipson, 2001) have also shown that the execution costs of buy versus sell orders are different. For example, Saar (2001) predicts that institutional buy orders are more difficult to execute as they are perceived to be more informed than large sell orders.

Jones and Lipson (2001), on the other hand, argue that buy orders tend to be cheaper to execute than sell orders. To capture any potential differences between buys and sells, we include a dummy variable for buy orders.

Keim and Madhavan (1996) find that establishing a long (short) position when prices are rising (falling) is more difficult due to potential information leakage before the order starts trading. We control for this pre-trade momentum by including the signed return of the stock during the 10-minute window before the first child order execution. Similarly, volatility in the market influences the algorithms' trading strategy – for instance, how finely should a parent order be sliced or how aggressively should the order be worked in the market – as they seek to minimize the cost and risk of execution (Engle et al., 2012). Hence, we include pre-trade volatility, defined as the standard deviation of ten-millisecond quote midpoint returns during the 10-minute period before the first child order execution, as a control variable.

Previous studies have also shown that execution costs are affected by the fund manager's identity (Chan and Lakonishok, 1993, 1995) and their investment style (Keim and Madhavan, 1997; Jones and Lipson, 1999). Keim and Madhavan (1997) also observe substantial variation in trading costs within the same investment style which they attribute to trading skill which is largely unobservable (see also Anand et al., 2011). These variables affect institutional execution costs as they are related to investors' need for immediacy, order aggressiveness, level of informational advantage, etc. While we cannot directly observe fund manager identity and investment style, we include several control variables that capture differences in trading behavior originating from heterogeneous investment styles.

To capture the degree to which an institutional investor is informed, we include the long term price impact as measured by the trade direction-signed return from the quote midpoint immediately before the parent order begins trading to the closing quote midpoint one day after the last child order execution. When determining their execution strategy, investors' urgency to trade likely influences how patient or aggressive they are while trading. For example, Keim and Madhavan (1997) find that value (technical) traders rely heavily on limit (market) orders and have lower (higher) transactions costs. Patient institutional investors may be able to lower their transaction costs by spreading more child orders over a longer period of time and thereby more easily hide among other traders. They can also trade less aggressively by using passive orders and thus earn the bid-ask spread. Hence, we include the trade duration (measured as the number of exchange trading hours between the first and the last child order execution), the percentage of volume executed through aggressive orders, and the number of child order executions in a parent order. Institutions may also choose the trading venue as part of their execution strategy. To capture any differences between trading costs associated with the choice of different trading venues, we include the percentage of volume executed on the three MTFs.

Finally, one potential channel through which colocation likely helps institutions is by allowing them to mimic HFT strategies and to minimize the sensitivity of their trading costs to trading against HFT. To test for this possibility, we include three measures capturing the interactions of HFT activity and institutional investors' trades: the fraction of the order executed against all HFTs, aggressive (liquidity-taking) HFTs, and passive (liquidity-providing) HFTs. Separating HFT into liquidity taking and liquidity supplying HFT allows us to capture the impact on execution costs associated with different HFT strategies. For example, liquidity supplying (consuming) HFTs are more likely to trade against (with) "the wind" (Van Kervel and Menkveld, 2019).

4 Estimation Approach

We use order level regressions to examine the determinants of institutional execution costs and particularly whether the use of colocation services allows members to lower the execution costs for their trades executed in an agency and a proprietary capacity. We employ the following panel regression setup for this purpose:

$$\begin{aligned}\text{Execution Cost}_{istk} = \alpha &+ \beta_1\text{TradeChar}_{istk} + \beta_2\text{Agency}_{istk} + \beta_3\text{Colo}_{is} \\ &+ \beta_4\text{Colo}_{is} \times \text{Agency}_{istk} + \beta_5\text{HFT}_{istk} + \beta_6\text{ColoHFT}_{istk} \\ &+ \beta_7\text{Agency}_{istk} \times \text{HFT}_{istk} + \beta_8\text{Agency}_{istk} \times \text{ColoHFT}_{istk} \\ &+ \mu_{st} + \eta_k + \nu_i + \varepsilon_{istk}\end{aligned}$$

where for parent order k on day t in stock s by exchange member i, *TradeChar* is a vector of the order and execution characteristics defined in Subsection 3.2, *Agency* indicates agency orders, *Colo* indicates whether an exchange member is colocated on the stock's primary listing venue or Turquoise[10], *HFT* is a vector containing the fraction of the parent order executed against all, passive, or aggressive HFT counterparties, and *ColoHFT* is the fraction of the parent order executed against an HFT on a venue where the exchange member is colocated. Stock-day fixed effects μ_{st} capture any unobservables affecting the execution cost for a stock on the day the order starts trading. For example, trend-chasers, momentum (Jegadeesh and Titman, 1993) and contrarian traders (De Bondt and Thaler, 1985), trade stocks based on their past performance. Quarter-hour fixed

[10]As discussed above, we use colocation on Turquoise as a proxy for colcation on the MTFs.

effects η_k capture systematic differences in execution costs depending on when during the trading day the execution begins. This includes differences in execution costs likely arising due to distinct patterns in intraday price formation.[11] For example, Madhavan et al. (1997) find that intraday patterns in liquidity and volatility are consistent with a decreasing level of informational asymmetry and increasing inventory costs through the day. Another example is the potential impact of the increased trading activity around the US market open. Exchange-member fixed effects ν_i capture the impact of broker skill and other unobserved effects associated with the individual brokers, for example differences between high-touch versus low-touch brokers. We estimate the above model with and without exchange-member fixed effects to separately understand the differences in execution costs by trading capacity and colocation within individual brokers. In all models, standard errors are clustered by exchange member and stock. We winsorize all variables, except the dummy variables and those expressed in percentages, at the 99.5% level.

A potential concern in our analysis is that our regression design does not fully control for the differences in trading motives or investment styles across agency and proprietary orders. While investors' trading motives are not directly observable in our dataset, our choice of control variables and fixed effects indirectly controls for trading motives and differences in execution strategy originating from heterogeneous trading motives. Furthermore, if trades are observationally indistinguishable in our data, they are likely also hard to distinguish by other market participants, whose response ultimately, apart from observable execution characteristics, determines execution costs. It appears unlikely that unobserved trading motives would affect execution costs.

[11] In untabulated results, we examine the distribution of orders throughout the trading session and do not find any large differences in when agency and proprietary trades begin.

A second possible concern in our regression design could be that the relationship between the observable trade characteristics and execution costs is non-linear and differs by trade capacity and brokers' use of colocation due to an imbalance in the covariates. For example, larger orders are more difficult to execute and are generally associated with higher execution costs. However, the exact relationship, whilst apparently concave (Keim and Madhavan, 1996, 1998), is unknown. While the square root law is widely accepted in the industry (see, for example, Torre, 1997), Almgren et al. (2005) and Zarinelli et al. (2015) obtain evidence against it.

We address this concern by using inverse propensity score weighting (IPW) in our regressions. This estimator combines weighting and regression adjustment and has the doubly-robust property (Robins and Rotnitzky, 1995; Imbens and Wooldridge, 2009), meaning that it is consistent even if one of the models for the propensity score or the outcome regression is misspecified. While this approach has occasionally been used in the finance and economics literature in the case of binary treatments (see e.g. Bird, 2018; Van Biesebroeck et al., 2015), our context entails multiple treatments: the exchange members' colocation status, and the trading capacity (agency vs. proprietary).[12,13]

We thus follow the literature started by Imbens (2000), who extends the binary treatment propensity score methodology to multiple treatments. In our case, there are two binary treatment variables forming four treatment categories with no natural ordering: $(\bar{C}, \bar{A})$, $(C, \bar{A})$, $(\bar{C}, A)$, (C, A), where C and $\bar{C}$ denotes colocation and non-colocation and A and $\bar{A}$ denotes agency and proprietary trades, respectively. In the first stage, we estimate the propensity score for the four treatment categories using a multinomial logit

[12] Another commonly used doubly-robust approach employing propensity scores uses matching. While matching is possible even in the multiple treatment case (Linden et al., 2016), finding good matches becomes increasingly difficult in finite samples.

[13] We report results from unweighted panel regressions in the appendix. The results do not qualitatively differ from those obtained using the doubly-robust estimator.

model, where we include as independent variables the same vector of market, trade, and execution characteristics described above. Similar to Uysal (2015), the inverse of the predicted propensity score for each of the four respective treatment categories is then used to weigh the observations in the second stage regression where we again control for market, trade, and execution characteristics as well as stock-day, quarter-hour, and, in some of our analyses, exchange member fixed effects. Since this is a two-step estimation approach with no known analytical expression for the standard errors, we estimate these using bootstrapping with 1,000 iterations.

5 Descriptive Statistics

5.1 Stock Characteristics

Table 1 shows the summary statistics for the 83 out of 86 stocks in our final sample which have parent orders. We also report the summary statistics for each market capitalization tercile. The stocks have an average market capitalization of €8.75 billion, daily continuous trading volume of €29 million, and a quoted bid-ask spread of 20 bps. Trading activity is highly fragmented across the four main venues with the primary listing exchange responsible for 62% of the market share and the three largest MTFs contributing the remaining 38% for the average stock. However, there is substantial cross-sectional variation across all these dimensions as evidenced by the difference in mean (and median) values across the three size groups. Stocks of larger firms have higher trading volumes, lower bid-ask spreads, and their trading activity is more fragmented. Finally, according to Refinitiv data, the four lit venues in our data jointly comprise more than 95% of the total lit trading.

Insert Table 1 about here

5.2 Exchange Member Characteristics

We identify 11,724 parent orders executed by 139 exchange members in 83 stocks from 8 countries. Table 2 provides exchange-member level summary statistics separately for all exchange members in our sample (Panel A) and for those who trade both in a proprietary and agency capacity (Panel B).

Insert Table 2 about here

The average exchange member executes 84 parent orders in about 14 stocks from 3 countries totaling €48.1 million during our sample period. There is substantial heterogeneity across exchange-members: some are active in only three (one) stocks (country), whereas others are active in 54 (eight) stocks (countries). 36 exchange-members engage in both agency and proprietary trading and 60 (43) members specialize in agency (proprietary) trading. However, the dual capacity members are much more active. The average exchange member trading in a dual capacity trades more than 29 stocks from 5 countries totaling €138.3 million during our sample period. This translates to such exchange-members accounting for more than 70% of all the parent orders both in terms of order count and total trading volume.

35% of all exchange members and two-thirds of those acting in a dual capacity execute some fraction of their institutional orders on the three MTFs. This may seem surprising considering the best execution obligations imposed on brokers by EU regulations, in particular by the Markets in Financial Instruments Directive (MiFID).[14] However,

[14]Contrary to the US, where the obligation to provide best execution rests largely with trading venues, in the EU, brokers are obligated to provide best execution to their clients.

broker-dealers enjoy substantial flexibility while ensuring compliance with these rules. For example, MiFID allows them to define best execution in terms of price, costs, speed, likelihood of execution and settlement, size, nature or any other consideration relevant to order execution. At the same time, brokers can apply these factors differently to different clients, orders, instruments, and venues. It is also not mandatory that brokers are connected to multiple trading venues.[15]

The mean and median number of primary markets in which the average exchange member is colocated is 0.6 and 0, respectively, indicating that the majority of members in our sample choose not to colocate. In fact, only 30% of the exchange members use any colocation services. The vast majority of these members choose to colocate on one of the primary listing exchanges as opposed to on the MTFs. Conditional on being colocated anywhere, exchange-members are on average colocated on 2.2 venues. Exchange-members trading in a dual capacity are more likely to colocate on the primary markets and the MTFs. They are also colocated on more trading venues compared to exchange-members trading exclusively in an agency or proprietary capacity. Specifically, 56% and 25% of all exchange-members trading in dual capacity are colocated on the primary markets and MTFs, respectively. Unconditionally, such members on average colocate on 1.3 primary markets and, conditional on being colocated anywhere, they are colocated on 2.8 venues.

5.3 Parent Order Characteristics

Table 3 provides summary statistics at the parent order level separately for the complete set of orders and for those executed in an agency and proprietary capacity. The table also reports the mean differences between agency and proprietary orders, the associated

[15] See CESR (2007) for further details.

t-statistics, and the standardized mean difference as a measure of the economic magnitude of the differences.

Insert Table 3 about here

Panel A shows that, for approximately 53% of all parent orders, the executing broker is colocated on the stock's primary exchange or on the MTFs. The difference between these figures for agency and proprietary orders (51% versus 55%), while statistically significant, is economically small.

Panel B shows that there are roughly equal numbers of buy and sell orders. The average trade size is 570 thousand Euro and $Information$, the average long-term price impact of trades, amounts to -9 bps suggesting that, on average, a parent order is uninformed. These numbers do not substantially differ between trades executed in the different capacities as indicated by the insignificant differences.

Panel C describes the parent order execution characteristics. The execution lasts on average about 5 exchange trading hours and, while the difference between agency and proprietary trades is statistically significant, its magnitude is rather small. There is a substantial difference between the two capacities in their choice to supply or consume liquidity: 44% of an average agency trade consumes liquidity, whereas this percentage is only 39% of proprietary trades. The difference concerning the choice of trading venue is even larger: only 17% of the average agency order executes on the MTFs, whereas the corresponding percentage for proprietary orders is 39%.

Panel D reports the execution costs of the average parent order, the effective half spread paid (earned) by the aggressive (passive) executions that are part of an average parent order, and finally the one-minute price impact associated with every passively and aggressively executed trade. The execution cost, our main variable of interest, is

−4.46 bps on average. The negative average may be due to the fact that the average parent order in our sample is uninformed as evidenced by the negative value of the *Information* variable and traded passively as evidenced by the *Aggressiveness* variable. For instance, Keim and Madhavan (1998) find that value (technical) traders who trade passively (aggressively) end up with negative (positive) execution costs. Furthermore, based on the regression coefficients estimated later in this paper, the expected execution cost for an agency order with zero information and an even split between liquidity-consuming and -providing executions is positive. However, average execution costs are significantly smaller for proprietary orders than for agency orders. The difference of more than 4 bps, while not large relative to the variation in execution cost between individual trades, is economically large and statistically significant. The average aggressive (passive) trade incurs (earns) a half-spread of 4.97 bps (3.62 bps). The average trade when executed aggressively incurs a lower cost for proprietary trades vis-à-vis agency trades (4.75 bps vs 5.20 bps). At the same time, the average passively executed proprietary trade earns a larger half spread than the average passively executed agency trade (3.74 bps vs 3.49 bps). The better child order execution outcomes measured in terms of effective spreads can be further extended to the average price impact as well. The average price impact of an aggressively executed order is higher for agency trades as compared to proprietary trades (3.75 bps vs 3.25 bps). The corresponding numbers for passive executions are nearly identical (−4.68 bps vs −4.67 bps). The difference in effective spread and price impact between agency and proprietary trades provides the first evidence of the execution performance of underlying algorithms. In section 7, we test whether differences in these (and other) variables hold using the empirical model described in section 4.

Finally, Panel E reports the HFT interaction statistics. Agency orders trade about 30% of their volume against HFT firms, whereas the number for proprietary orders is about 33%. This difference is significant and consistent with proprietary orders being executed to a larger extent on MTFs, where HFTs are generally more active than on the primary listing exchanges. The average parent order is approximately twice as likely to interact with aggressive HFTs as compared to passive HFTs. However, agency orders execute to a slightly lesser extent against aggressive as opposed to passive HFTs (65% vs 68%). These statistics are broadly consistent with the usage of aggressive orders in Panel C. For instance, roughly two-thirds of the average parent order is executed passively and roughly two-thirds of the average parent order's HFT interactions are against aggressive HFT. Similarly, the average agency order is more aggressively executed compared to the average proprietary order and is also more likely to interact with passive HFT counterparties. These statistics suggest that the algorithmic decision to supply or consume liquidity does not substantially influence the extent to which the parent order interacts with HFT firms.

To conclude, agency and proprietary executions are largely similar in terms of their order characteristics, duration, and the use of exchanges' colocation services. However, they differ with respect to their choice of trading venue, level of aggressiveness, and interactions with HFT firms. We overcome this imbalance via the doubly robust approach of controlling for all these variables in our analyses in combination with inverse propensity weighting.

6 Parent Order Results

This section describes the determinants of execution costs of large orders. Our main focus is on understanding how execution costs differ by the capacity in which the exchange member trades an order and the use of colocation. Additionally, we consider the relation between execution costs and interactions with HFTs.

6.1 Baseline Analysis

Execution costs are positively related to trade difficulty (Keim and Madhavan, 1997). For example, orders that are large (relative to the daily volume of a stock) are more difficult to execute. A market participant acquiring a large position may prefer to trade patiently over a long period while relying on limit orders (to avoid crossing the bid-ask spread) and minimizing executions on MTFs to avoid being back-run by HFTs. However, if a market participant is impatient, possibly because it possesses short-term information, it may have to trade aggressively using marketable orders while accessing all sources of liquidity. We examine this tradeoff by regressing execution costs on the predictors described in Subsection 3.2. Table 4 contains the baseline results.

Insert Table 4 about here

As expected, transaction costs increase with parent order size. Depending on the regression specification, a 0.1 unit increase in log trade size is associated with between 0.26 and 0.33 bps higher execution costs. As trade sizes vary substantially and can be very large in some cases, this effect is economically significant. The total trading volume in the market, *Market Trading*, is negatively related to execution costs as higher trading volume introduces more noise in the signal generated by the parent order executions. A

0.1 unit increase in log total volume during the parent order's lifetime is associated with 0.34 bps lower execution costs.

The execution costs for buys are around 2 bps higher than for sells, though the effect is statistically insignificant.

Pre-trade volatility, measured as the standard deviation of ten-millisecond quote midpoint returns over the ten minutes before the first child order execution, predicts a 17 bps difference in parent order execution costs for every 1 bps change in volatility, however the impact is statistically insignificant. Note that the mean and standard deviation of volatility are both less than one-tenth of one basis point. The stock return over the ten minutes before the trade has no explanatory power across all specifications.

The permanent information content of the trade is, as expected, positively associated with the execution cost. A 10 bps increase in *Information* is associated with approximately 1.5 bps higher execution costs. The time it takes to complete a parent order is negatively associated with transaction costs and the association is statistically significant. Specifically, working a parent order for one additional hour is associated with a 1.7 bps lower execution cost. This is because, keeping parent order size constant, duration is inversely related to the institution's participation rate and, consequently, negatively associated with transaction costs. However, this effect becomes somewhat smaller and statistically weaker once we control for the stock's total trading volume (*Market Trading*) during the parent order's life time, which together with the child order size determines the participation rate. Trading impatiently by using aggressive (i.e., marketable) orders is associated with higher transaction costs. A trade that is executed with a 10 percentage points higher share of liquidity taking orders is associated with a 3.1 bps higher execution cost.

The number of child order executions is also significant in explaining parent order transaction costs: a 0.1 unit increase in log child order executions is associated with a 0.41 bps increase in execution costs, though this effect decreases slightly once we control for the fraction of a parent order traded on MTFs, where individual order executions are generally smaller. Considering that the size of individual child order executions, and therefore their number, is endogenously related to the liquidity available in the limit order book, even in the presence of stock-day fixed effects, the direction of any causality between the number of child orders and execution costs is unclear. The situation is similar when interpreting the effect of the volume executed on MTFs because the choice of venue partially depends on the liquidity available in the primary market. The coefficients suggest that shifting 10% of the parent order away from the primary market and towards the MTFs is associated with a 0.7 bps increase in execution costs.

6.2 Trading Capacity, Colocation, and Interaction with HFT

In Table 5, we consider the effects of exchange members' execution capacity, whether the exchange member executing the parent order is colocated on a venue where the stock trades, and the fraction of a parent order that executes against liquidity providing and consuming HFTs. We report the results from panel regressions with stock-day and quarter-hour fixed effects, and the variables included in column (4) of Table 4 as untabulated controls. We center all interacted continuous variables at zero.

Insert Table 5 about here

We find that, after including all baseline control variables, orders executed in an agency capacity are substantially more expensive than proprietary orders. The difference in execution costs is economically meaningful at about 4.5 bps, or more than 50% of the quoted spread of a typical large cap stock in our sample. Column (2) shows that additionally including a colocation dummy does not unconditionally explain any variation in execution costs. In columns (3) and (4) we add an interaction term that identifies the effects of colocation on the execution costs of agency versus proprietary orders. The main effect of colocation, now representing the effect for proprietary orders, turns significant and shows an execution cost reduction of around 6 bps, whereas colocation for agency trades is associated with 7.2 bps higher execution costs compared to proprietary orders, suggesting that agency orders do not benefit from exchange members' subscription to colocation facilities.

We next include trading volume against HFTs and find that an additional 10% of an order traded against HFTs is associated with an increase in execution costs by 0.9 bps. When splitting HFT into liquidity taking versus liquidity providing executions, we find that they have opposite effects on transaction costs: trading an additional 10% of an order against aggressive HFT is associated with around 3.7 bps higher execution costs, whereas the effects of trading the same amount against passive HFT is around −3.0 bps.

We then include the fraction of trading volume against HFT on a venue where the exchange member is colocated and find that both the adverse effects of aggressive, and the beneficial effects of passive, HFT are reduced when the exchange member is colocated. The adverse effect of aggressive HFT is reduced by around 50% whereas the beneficial effect of passive HFT is smaller by more than 80%. This indicates that execution costs depend on the type of counterparty to a lesser extent for colocated market participants, allowing them to obtain execution costs that are less sensitive to the nature of the counterparty. The net impact of HFT on orders originating from colocated exchange members nevertheless remains positive due to the higher magnitude of the effect of aggressive HFT on execution costs and due to parent orders in our sample being twice as likely to trade against aggressive HFTs than passive HFTs.

Finally, we interact the fraction of trading against HFT on a venue where the exchange member is colocated with the agency dummy to examine whether agency orders not only generally fail to benefit from colocation but possibly also see a smaller effect of colocation on the costs when facing HFTs. However, the coefficients suggest no significant effects when trading against HFTs.

6.3 Within Exchange Member Variation in Execution Costs

Despite all the covariates and fixed effects we employed in the previous analyses, it might be that unobservable differences across exchange members drive our results. This includes differences in the type of colocation facilities, such as access speed and capacity, chosen by individual members as well as other technological and connectivity differences. For example, as of June 2022, Deutsche Börse allows exchange members to configure their colocated infrastructure based on power requirements, type of market data, and other connectivity options.[16] Finally, differences in trading skills, specifically the quality and choice of order splitting and routing algorithms, might also explain part of our results.

To address these concerns, we conduct an alternative analysis in Table 6 that, in addition to stock-day and quarter-hour fixed effects, includes exchange member-fixed effects.[17] While the inclusion of the additional fixed effects eliminates the variation in colocation on Turquoise, we retain the colocation variable that captures exchange members' decision to colocate on individual primary markets, which we denote $Colo_{PM}$. This is because

[16]Further details on Deutsche Boerse's colocation service are available at https://www.xetra.com/xetra-en/technology/co-location-services.

[17]We do not report the baseline results with exchange-member fixed effects as these are qualitatively similar to the results in Table 4.

brokers are not colocated on all primary venues. The identification of the colocation effect now stems only from those exchange members that execute parent orders on primary markets where they are colocated and others where they are not colocated. Similarly, the identification of the differences between execution costs for agency and proprietary orders now comes from exchange members executing orders in both capacities. Employing exchange-member fixed effects in combination with our control variables and IPW effectively allows us to estimate the impact of colocation for agency versus proprietary orders for similar orders originating at the same exchange-member.[18]

Insert Table 6 about here

Similar to the previous analyses, parent orders executed in an agency capacity incur higher execution costs. Compared to the earlier results, the size of the coefficient increases to 9.2 bps. This finding implies that, while agency executions across all member firms incur higher execution costs, execution costs of those firms that specialize in agency or proprietary executions differ less compared to the differences between agency and proprietary orders originating from exchange members that trade in a dual capacity.

After including the colocation dummy and its interaction with the capacity dummy, the results are again similar to those obtained without using exchange member-fixed effects: proprietary trades benefit from the use of colocation, whereas this is not the case for agency trades. Specifically, the effect of colocation on the execution costs of proprietary orders is −6.3 bps. However, when these colocated brokers execute agency orders, they have significantly higher execution costs with a coefficient of 7.8 bps. The effect of the agency dummy variable is statistically significant at 5 bps, which suggests that agency orders originating from dual-capacity exchange members have higher execution

[18]The reduction in effective sample size necessarily reduces the estimations' statistical power.

costs compared to proprietary orders executed by the same firm even when the broker is not colocated.

The unconditional effects of parent orders interacting with HFT firms remain qualitatively unchanged. In aggregate, trading against HFTs is associated with higher execution costs. The volume transacted against aggressive HFT orders is associated with higher execution costs whereas the volume against passive HFT orders has the opposite effect. Compared to the results without exchange-member fixed effects, the size and significance of the coefficients for the interaction of colocation with aggressive and passive HFTs retain their signs whereas the size and statistical significance changes somewhat. The benefit enjoyed by a non-colocated broker from trading against passive HFTs is somewhat larger, whereas the interaction effect between colocation and passive HFT is larger and now significant. The two effects cancel out suggesting that sophisticated traders do not systematically experience large differences in execution costs based on the kind of counterparties they trade with.

In conclusion, the main results do not appear to be sensitive to the chosen regression specifications. Colocation helps proprietary traders reduce their transaction costs and avoid losses to aggressive HFTs, but these benefits are limited to proprietary executions.

6.4 Analysis of Individual Member Fixed Effects

While our previous results document that, on average, the benefits of colocation in the form of lower execution costs are limited to proprietary executions, they leave unanswered the question whether this phenomenon is common or driven by a small number of outliers among the brokers. To answer this question, we perform regressions similar to the above, except that we include a larger set of dummy variables to study the cross-sectional distribution of within-broker differences in execution costs between agency and proprietary trades. In particular, in addition to the baseline control variables and stock-day and quarter-hour fixed effects as in the regressions in Table 4, we include dummy variables at the broker-capacity-colocation level. There are 18 brokers trading in both capacities on venues where they are colocated. For each of these brokers, we compute the difference between the fixed effects of agency and proprietary trades, respectively, for trades executed on a venue where the broker is colocated.

Insert Figure 1 about here

Figure 1 shows the estimates and error bars of this difference for the individual brokers. Execution costs are higher for agency orders for 15 of the 18 brokers and for 5 of them the difference is statistically significant at the 10% level. At the same time, none of the 3 differences in the opposite direction are statistically significant. A non-parametric Wilcoxon signed-rank tests provides strong evidence that agency orders do not obtain the same benefit from colocation as do proprietary orders, with a p-value of 0.0021. In summary, the higher execution costs of agency compared to proprietary trades executed by the same colocated broker can be observed for most dual capacity brokers in our sample. Overall, these results show that our main findings are not driven by a small subset of these brokers but the result of likely similar choices made by brokers and their institutional customers.

7 Child Order Submission and Execution Outcomes

The results reported in section 6 raise the question as to *how* agency trades, in particular those executed via colocated brokers, obtain execution costs that are higher than comparable trades executed by exchange members in a proprietary capacity. We here do not aim to establish causal effects of any particular characteristics of the order submission strategies on parent order execution costs. This would require reengineering the logic of the order execution algorithms, a task that appears infeasible, considering the fact that we observe data on a broker level and each broker likely employs multiple algorithms.[19] Instead, we consider the algorithms' ability to monitor the order books and the execution quality of the individual child orders and how these measures relate to the brokers' colocation status and the capacity in which they execute orders.

7.1 Order Book Monitoring

Subscribing to exchanges' colocation facilities should allow brokers to better monitor the order book at high frequencies and employ order execution algorithms that quickly respond to changing market conditions. For instance, it can allow brokers to rapidly revise a passive child order after submission if the order becomes stale due to price changes, thereby resulting in improved fill ratios and/or reduced price impact costs. In this subsection, we provide evidence indicative of the improved monitoring ability by analyzing order flow periodicity and order-to-trade ratios (OTR) for orders submitted in both capacities and with or without the use of colocation technology.

Bacidore (2020) argues that *"one tremendous avoidable source of latency stems from algo provider's decision to use 'timer-based' instead of 'event-based' processing.[...] A timer-based algorithm 'wakes up' periodically, e.g., every 500 milliseconds, samples the state of the market, and then takes action before beginning another 500-millisecond slumber[...]."* The relatively higher latency in the absence of colocation may be a reason for

[19]For a detailed analysis of the execution algorithms offered by a single broker, see Beason and Wahal (2020).

brokers to employ timer-based strategies. Figure 2 shows the the frequencies of orders submitted during different seconds within a minute separately for the four combinations of colocation/no colocation and agency/proprietary orders. The plots show deviations of the logarithm of the number of order submissions from their mean. For all four groups, the largest abnormal number of order submissions occurs in the first second of a minute, and the effect is larger for agency compared to proprietary orders, and for non-colocated compared to colocated orders. While we cannot rule out the possibility that (some of) the excess order volume may be in response to other market participants' high activity at those times, the plot does suggest the existence of algorithms using clock-time scheduling. There are also spikes at the other 10-second intervals within the minute for both agency and proprietary colocated orders. These spikes are more pronounced for agency orders, which is indicative of agency algorithms being less responsive to market events. The lower periodicity observed for non-colocated orders is likely due to the presence of high-touch trading in this category, which introduces noise in the observed periodicity. In untabulated tests, we show that the observed differences at second 0 hold after employing stock-fixed effects or stock- and broker-fixed effects, whereas the coefficients for those at seconds 10, 20, 30, 40, and 50, are of the expected sign though not statistically significant.

Altogether, the figure and the statistical tests imply that there is more periodicity in the order submission of agency versus proprietary colocated orders. The presence of such predictable patterns in order submissions in calendar time, which has also been observed in earlier studies (Brugler, 2015; Sağlam, 2020), might contribute to poor execution performance, as such patterns can be anticipated by HFTs engaging in back-running behavior. For instance, Sağlam (2020) finds that the use of time- and volume-based execution algorithms leads to predictable patterns in order flow which are correlated with higher execution costs. Conversely, a reduction in predictability is associated with lower execution costs. While the above analysis reveals the presence of such predictable patterns for parent orders executed with and without colocation in both capacities, the disproportionately higher predictability of colocated agency orders may help explain the higher execution costs for such orders.

Next, we analyze the differences in the OTR – defined as the ratio of the number of order submissions to the number of child order executions – by capacity and use of colocation. Specifically, we consider whether the OTR systematically differs by the type of parent orders by regressing parent orders' OTR on the same predictors as in the previous analyses. OTRs are generally used to track algorithmic and high-frequency trading activity in electronic markets (see, for example, Hendershott et al., 2011). The results in Table 7 show that there is no statistically significant difference between agency and proprietary orders in the absence of colocation.[20] The results without broker-fixed effects in column (1) show that proprietary colocated orders feature a significantly higher OTR than non-colocated ones, which is consistent with colocation enabling brokers to more successfully manage their orders' positions in the limit order book. However, this effect is absent for colocated agency orders, with a coefficient that, albeit only weakly statistically significant, nearly offsets the positive coefficient for colocation. The within-broker differences in OTR between colocated and non-colocated proprietary orders reported in column (2) are positive, though smaller than in column (1) and statistically insignificant. This reduced effect is consistent with the idea that brokers that colocate anywhere employ relatively sophisticated algorithms across trading venues regardless of their colo-

[20] The table is based on observations for 80 of the 83 sample stocks. Due to only intermittent access to the data, we will update the table with results for the complete sample in the next revision.

cation. This would allow them to actively manage their orders to some degree even where they are not colocated. However, OTR is significantly lower for colocated agency orders, which, somewhat surprisingly, results in colocated agency orders having a lower OTR than non-colocated agency orders. However, the latter difference (untabulated) is not statistically significant.

Altogether, this subsection provides evidence suggesting that the algorithms colocated brokers use for their proprietary orders materially differ from those used for customer execution. The latter feature higher periodicity and, in particular, a lower OTR, which is indicative of a less active management strategy of child orders, and likely contributes to higher parent order execution costs.

7.2 Child Order Execution Quality

Having established some differences between colocated agency and proprietary orders with respect to their child order submission behavior, in this subsection, we turn to their execution quality. When executing a child order, an institutional investor would like to accomplish two goals: first, low execution costs of individual child orders, and second, to minimize the extent of adverse price changes that would make subsequent child order executions more expensive. As a measure of how well an order performs with respect to the first goal, we compute parent order level averages of the effective spreads for the individual child executions that make up a given parent order. We disaggregate the analysis into spread costs for aggressive versus passive order execution.

Panel A of Table 8 contains the results. Note that the number of observations in this table is smaller than in the previous ones because a parent order is included only if it contains at least one aggressive (passive) child order execution. Column (1) shows that colocation reduces the spread paid by liquidity consuming orders, and this effect does not significantly differ between proprietary and agency orders. However, agency orders pay wider spreads regardless of the use of colocation, suggesting that execution algorithms used for agency trades may generally be inferior to those used for proprietary trades. This cost disadvantage of 0.4 bps amounts to more than half of the benefit colocation provides. However, it makes up only a small part of the execution cost disadvantage agency parent orders suffer. When we consider within-broker variation in column (2), we do not find statistically significant differences between trades in stocks listed on an exchange where a broker is colocated and where it is not, and, though the coefficient estimate is of the expected sign, it is of substantially smaller magnitude than in the analysis without broker fixed effects. This finding is consistent with that in the previous subsection that brokers' execution capabilities may to a significant extent translate across exchanges, and that the use of colocation anywhere goes hand-in-hand with higher technological skills. The interaction effect of colocation with agency orders is also statistically insignificant, though the magnitude and sign suggest that any advantage of using colocation almost exactly cancels out for agency orders. Agency orders pay wider spreads regardless of colocation.

Turning to effective spreads earned in passive order executions, the negative coefficient on colocation in column (3) indicates that colocation is associated with wider spreads earned by the liquidity provider. The effect size is smaller than for aggressive orders, suggesting that speed and/or sophistication is more important for liquidity taking orders. We do not observe any significant differences between proprietary and agency orders. While the results obtained when we consider within-broker variation in column (4) are not statistically significant, agency orders generally obtain inferior execution, which, in this case, means they earn smaller spreads. This result suggests that dual capacity brokers manage agency limit orders worse than comparable proprietary limit orders, whereas this finding is not observable in the results exploiting differences across brokers. Compared to the analysis of aggressive orders, we observe that, in relative terms, colocation remains an economically more important predictor of effective spreads. While the effect size is somewhat smaller than in column (3), it does appear that speed, in addition to general technological sophistication, helps brokers earn wider spreads through facilitating timely responses to changing market conditions. The interaction effect of colocation and agency is statistically insignificant, though the point estimate amounts to a reduced benefit of employing colocation by more than half.

We now turn to the second goal institutional investors have with respect to minimizing their execution costs, i.e., avoiding price impact as a result of information leakage. Whereas in classic microstructure models the price impact is a reflection of the information content of a trade, investors splitting their trade among multiple child order executions desire to minimize their price impact so as to obtain beneficial trade prices in subsequent child trades. Thus, for aggressive orders, a low price impact points to a good execution outcome. For passive orders, a price movement against the direction of the order is usually interpreted as adverse selection and therefore undesirable. However, assuming that a trade happened at a certain price, an institutional trader would prefer experiencing a large price impact to obtain better prices for subsequent child orders. Yet, a limit order trader who does not manage the order effectively may get an execution when the order is stale, i.e., the price at which the child order trades may be disadvantageous as it would have been possible to trade at a better price. In that situation, while the price impact incurred may be large, the prices of subsequent child trades may not necessarily improve because the price would have moved anyway. Thus, for passive trade executions, it is unclear whether a large price impact should be interpreted as beneficial or harmful.

We measure price impact as the quote midpoint change from immediately before to either 1 or 60 seconds after a trade, signed by the direction of the institutional order. Similar to the effective spreads, we report the results separately for aggressive and passive orders.

Panels B and C of Table 8 show the results for price impacts at a one-second and one-minute horizon, respectively. For aggressive orders, the results show that colocation enables significantly smaller price impacts, with an effect size of about 0.7 bps within one second, which grows to 1.0 bps within one minute. Non-colocated agency orders are associated with statistically insignificant immediate and near-zero one-minute additional price impacts. However, the benefit to using colocation vanishes for agency orders. While the effect is slightly smaller and not statistically significant within one second, it grows to almost 1 bp, offsetting the advantage implied by the coefficient for colocation. The within-broker analysis yields similar results to those for effective spreads: the effects of colocation and its interaction with agency are small, whereas agency orders in general, regardless of colocation, result in price impacts that are higher by about 0.8 bps, within one second, though the coefficient shrinks to about 0.4 bps and becomes statistically insignificant for the one-minute horizon.

Columns (3) and (4) report the price impact results for passive orders. We note that a negative coefficient suggests a larger price impact from the institution's perspective or, put differently, a larger price move against the institution's trade direction. Column (3) shows that passive agency orders incur a larger price impact, with an effect size that rises to about 0.7 bps within a minute. As explained above, this could be an indication of trade execution at stale prices, and thus reflect poor execution quality. Alternatively, it suggests lower information leakage, potentially enabling successive trades at better prices. While we consider the former channel more likely, our estimations do not allow us to discriminate between the two interpretations. Proprietary colocated orders enjoy a price impact that is larger by about 0.8 bps after one second and 0.9 bps after one minute, whereas the positive coefficients for the interaction effect of colocation and agency show that the colocation effect nearly cancels out for agency orders. Based on the findings of the previous subsection and for spreads, it is likely that the effect of colocation for proprietary orders is reflective of the avoidance of information leakage. By contrast, agency orders do not enjoy the same benefit from colocation, and appear to be more exposed to stale executions, though the coefficient estimates alone do not firmly lead to a unique interpretation.

The within-broker analysis in column (4) shows that here, significant differences between non-colocated proprietary and agency orders do not exist. Colocation by itself does not statistically significantly predict price impact, though the effect size at a one-minute horizon is about half that observed in column (3). However, for colocated agency orders, the price impact is smaller, from the parent order's perspective, by 0.8 bps after one second and 0.5 bps after one minute. While the latter coefficient is not statistically significant, it is still sizable, when considering that this effect size accumulates over multiple child orders. To sum up, the effects of colocation are smaller within than across brokers, consistent with the previous results in this subsection.

In conclusion, the results on effective spreads and price impact contribute to our understanding of the results on parent order execution costs. Across brokers, in aggregate we observe poorer execution quality for agency orders and, in particular, colocated agency orders. Most of the results of the within-broker analyses are quantitatively and statistically weaker, but they tend to point toward poorer execution quality for agency orders irrespective of colocation. The OTR results in the previous subsection, indicating a less active management of child orders, complement the evidence described above and help explain the incremental parent order execution costs not captured by measures of immediate child order execution quality.

8 Conclusion

Speed dispersion across market participants is of importance because recent empirical and theoretical research has shown that HFTs can make large institutional trades more expensive, which, in turn, can lead to reduced price discovery and allocative efficiency of capital in the economy. Subscribing to exchanges' colocation facilities allows exchange members to submit orders and access the exchanges' market data feeds at low latencies. Based on a pan-European highly granular dataset comprising the main equity markets, we study how the execution costs of exchange members attempting to acquire or dispose of a large position in a proprietary or agency capacity vary with their use of the exchanges' colocation facilities.

Exchange members who colocate obtain lower execution costs for their proprietary orders but not for the orders of their buy-side customers. These results hold not only across brokers but also for the subset of brokers who execute large orders in a dual capacity. Furthermore, while institutional investors' execution costs are, on average, sensitive to trading against HFT firms, the magnitude of this effect is significantly smaller for colocated exchange members trading in a proprietary capacity. Investigations into the underlying trading patterns reveal that the above differences between customer and proprietary orders executed via colocated brokers coincide with differences in the monitoring and the execution quality of individual child orders.

We conjecture that the lack of benefit from colocation for customer orders is due to customers making inferior choices when selecting the most appropriate algorithm for a particular order or due to brokers using different algorithms for their proprietary and customer orders. While regulations do not require benchmarking the execution costs of orders originating from buy-side customers to the brokers' own executions, this comparison could be considered a natural approach to evaluating best execution.

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Figure 1: Difference between Agency and Proprietary Trades of Colocated Exchange Members

This graph shows the distribution of within-exchange member differences in execution costs in bps between agency and proprietary trades that a given exchange member executes on a trading venue where they are colocated. The estimates are based on regressions that include exchange member-capacity-colocation fixed effects in addition to baseline control variables and stock-day and intraday fixed effects. Standard errors are clustered by exchange member and stock and estimated using bootstrapping with 1,000 iterations. The ranges indicate 90% confidence intervals.

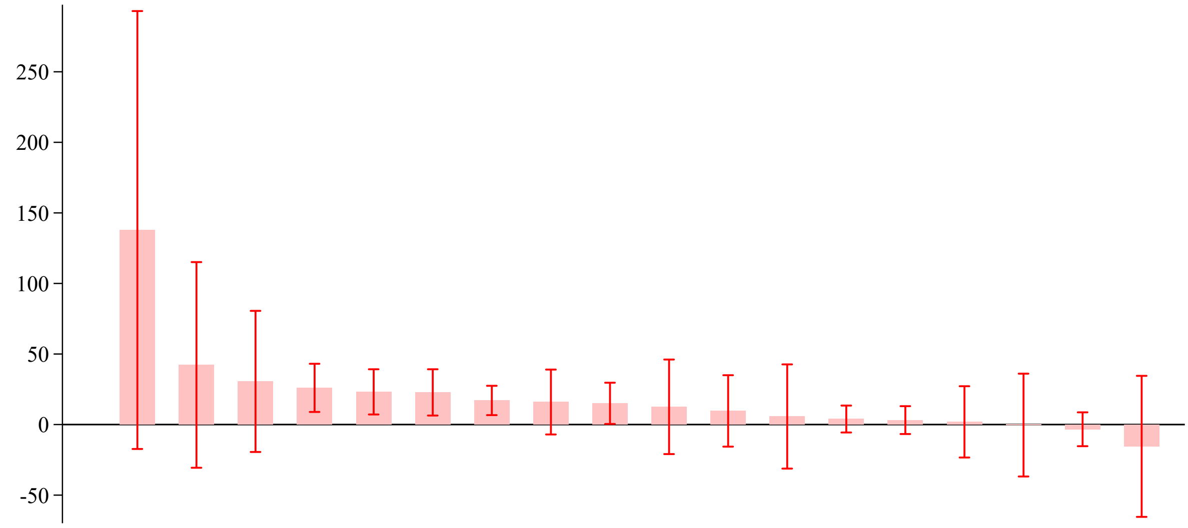

Figure 2: Periodicity in Order Submissions

This graph shows the distribution of child order submissions within a minute at the exchange member-stock-capacity level. The number of submissions is given in deviations of the logarithm of the number of order submissions at a given second from their overall mean. The horizontal axis indicates the second within a minute. The data is split according to whether an exchange member is colocated at an exchange where a given stock can be traded.

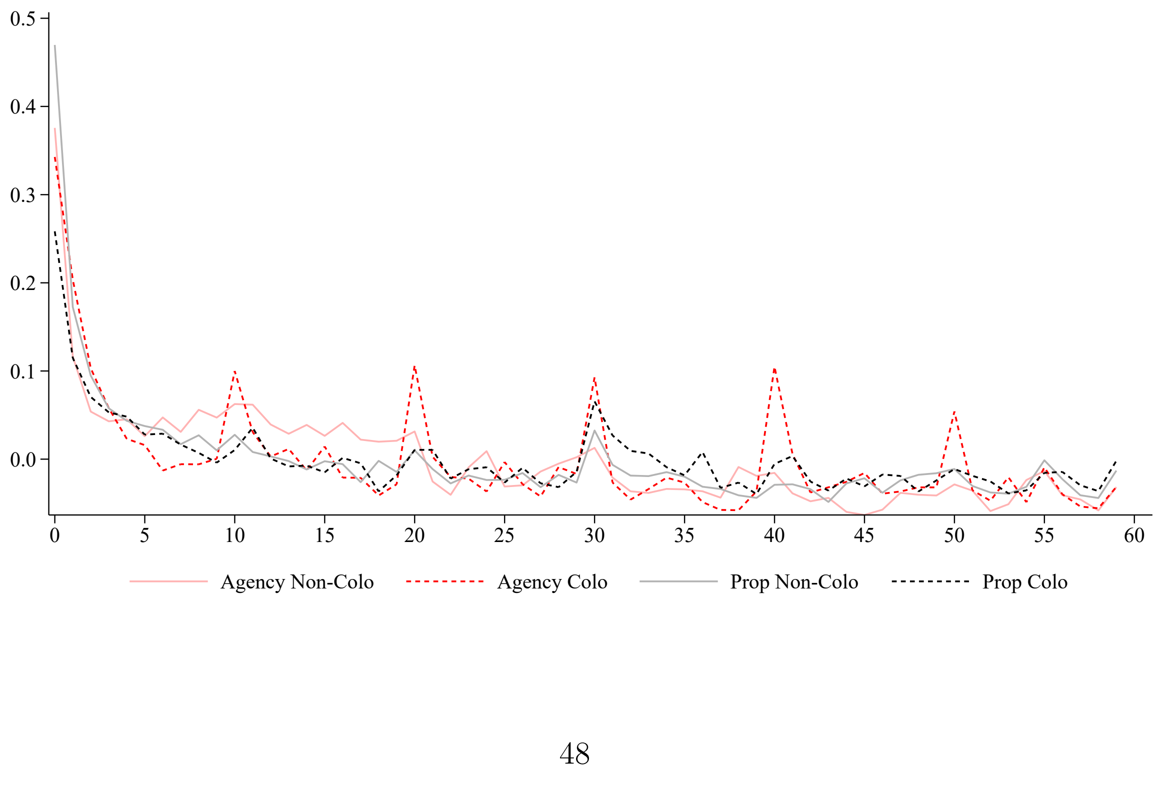

Table 1: Stock Summary Statistics

This table shows summary statistics on the 83 sample stocks. The stocks are sorted into terciles based on their average market capitalization during the sample period. *Market Cap.* is the average market capitalization in 1bn Euro. *Trading Value* is the average daily lit trading value across all exchanges in 1mn Euro. $Share_{PM}$ and $Share_{MTF}$ are the market shares of the stock's primary market and of the three MTFs combined, respectively, in percent. Spread is the average relative bid-ask spread at the primary market in percent.

Size	**Market Cap.**		**Trading Value**		$\mathbf{Share_{PM}}$		$\mathbf{Share_{MTF}}$		**Spread**	
	Mean	P50	Mean	P50	Mean	P50	Mean	P50	Mean	P50
Small	0.83	0.81	2.25	1.57	77.5	78.9	22.5	21.1	0.30	0.20
Medium	3.33	3.04	11.86	7.39	69.8	71.7	30.2	28.3	0.20	0.14
Large	22.57	9.72	74.53	36.44	60.6	57.4	39.4	42.6	0.09	0.08
Total	8.75	2.94	29.00	7.29	62.3	72.4	37.7	27.6	0.20	0.13

Table 2: Exchange Member Level Summary Statistics

This table shows exchange member level summary statistics. *Active Stocks* is the number of different stocks that the exchange member is actively trading. *Active Countries* is the number of different countries where those stocks are listed. *Total Volume* is the total trading value of parent orders in 1mn Euro. *# Orders* is the number of parent orders. *Active on MTF* is a binary variable set to one if the exchange member trades on any MTF, scaled by 100. *Agency* is the number of agency trades relative to all trades of an exchange member, in percent. *Colo*, *Colo* $_{PM}$, and *Colo* $_{TQ}$ are binary variables set to one if the exchange member is colocated on any venue, any primary market, or Turquoise, respectively, scaled by 100. *Colo* $_{\#\ PMs}$ is the number of different primary markets at which the exchange member is colocated. *Colo* $_{\#|Colo}$ is the number of different venues at which the exchange member is colocated conditional on being colocated at any venue.

	Mean	**P5**	**P50**	**P95**
Panel A: *All Exchange Members* (N = 139)				
Active Stocks	14.2	3.0	7.0	54.0
Active Countries	3.2	1.0	2.0	8.0
Total Volume	48.1	2.8	10.7	288.8
# Orders	84.3	11.0	29.0	497.0
Active on MTF	35.3	0.0	0.0	100.0
Agency	56.5	0.0	68.6	100.0
Colo	29.5	0.0	0.0	100.0
Colo $_{\text{PM}}$	28.8	0.0	0.0	100.0
Colo $_{\text{TQ}}$	8.6	0.0	0.0	100.0
Colo $_{\#\ \text{PMs}}$	0.6	0.0	0.0	4.0
Colo $_{\#\|\text{Colo}}$	2.2	1.0	1.0	6.0
Panel B: *Members Trading in Both Capacities* (N = 36)				
Active Stocks	29.4	6.0	23.5	68.0
Active Countries	5.3	1.0	6.0	8.0
Total Volume	138.3	9.5	78.1	489.8
# Orders	229.5	26.0	134.5	755.0
Active on MTF	66.7	0.0	100.0	100.0
Agency	51.5	20.3	49.8	86.0
Colo	55.6	0.0	100.0	100.0
Colo $_{\text{PM}}$	55.6	0.0	100.0	100.0
Colo $_{\text{TQ}}$	25.0	0.0	0.0	100.0
Colo $_{\#\ \text{PMs}}$	1.3	0.0	1.0	4.0
Colo $_{\#\|\text{Colo}}$	2.8	1.0	2.5	5.5

Table 3: Parent Order Level Summary Statistics

This table shows parent order level summary statistics. *Colo* is a binary variables set to one if the exchange member is colocated on the stock's primary market or the MTFs, scaled by 100. *Buy* is a binary variable for buy trades, scaled by 100. *Order Size* is the size of the parent order in 1k Euro. *Information* is the signed return from the quote midpoint before the first to the closing price one day after the last child order execution in bps. *Duration* is the trading-hours adjusted time the parent order is worked in the market. *Aggressiveness* is the volume of executions of marketable orders relative to the size of the parent order, in percent. *MTF* is the percentage of trade volume executed on an MTF. *Execution Costs* are the execution costs in bps. *Effective Half Spread* and *Price Impact* are the average effective half-spread and 1 minute price impact of all aggressive (liquidity-taking) and passive (liquidity providing) child order executions for a given parent order in bps. *Volume HFT* is the fraction of trade volume with an HFT counterparty in percent. *Volume aggr. HFT* is the fraction of trading volume where the counterparty is a liquidity-taking HFT in percent. The last columns show the results of t-tests for differences between agency and proprietary orders. $\frac{\Delta}{\sigma}$ is the difference standardized by the standard deviation of the overall sample.

	All Orders				Agency Orders				Proprietary Orders				Difference		
	Mean	P5	P50	P95	Mean	P5	P50	P95	Mean	P5	P50	P95	Δ	t-stat	$\frac{\Delta}{\sigma}$
Panel A: *Colocation and Capacity*															
Colo	52.95	0.00	100.00	100.00	51.35	0.00	100.00	100.00	54.47	0.00	100.00	100.00	3.12	(3.38)***	0.06
Agency	48.65	0.00	0.00	100.00	100.00	100.00	100.00	100.00	0.00	0.00	0.00	0.00			
Panel B: *Trade Characteristics*															
Buy	50.03	0.00	100.00	100.00	49.98	0.00	0.00	100.00	50.07	0.00	100.00	100.00	0.08	(0.09)	0.00
Trade Size	570.7	109.0	265.3	1,992.6	560.3	109.5	265.4	2,016.5	580.5	108.5	264.9	1,976.7	20.14	(1.15)	0.02
Information	-9.41	-330.08	-7.32	312.08	-6.71	-333.87	-3.41	311.50	-11.97	-322.22	-10.67	312.20	-5.27	(-1.38)	-0.03
Panel C: *Execution Characteristics*															
Duration	4.95	2.13	4.30	8.68	5.09	2.15	4.45	9.05	4.82	2.13	4.15	8.49	-0.27	(-5.47)***	-0.10
Aggressiveness	41.70	0.00	37.58	97.78	44.05	1.23	40.00	99.86	39.46	0.00	35.10	94.89	-4.59	(-8.28)***	-0.15
Child Order Executions	72.87	4.00	35.00	273.00	65.72	3.00	30.00	258.00	79.65	4.00	40.00	286.50	13.92	(6.92)***	0.13
MTF	28.39	0.00	3.63	100.00	17.20	0.00	0.00	100.00	38.99	0.00	28.40	100.00	21.79	(33.71)***	0.59
Panel D: *Execution Costs*															
Execution Costs	-4.46	-112.78	-2.60	102.69	-2.22	-110.35	-0.47	108.74	-6.59	-115.96	-4.56	94.91	-4.38	(-3.51)***	-0.06
Effective Half Spread$^{aggr.}$	4.97	0.63	3.30	14.46	5.20	0.69	3.39	14.77	4.75	0.60	3.16	14.09	-0.45	(-3.18)***	-0.06
Effective Half Spread$^{pass.}$	-3.62	-10.50	-2.48	0.74	-3.49	-9.72	-2.45	1.06	-3.74	-11.15	-2.50	0.49	-0.25	(-1.83)	-0.04
Price Impact$_{1min}^{aggr.}$	3.49	-4.52	1.97	15.78	3.75	-4.39	2.08	16.44	3.25	-4.65	1.89	15.07	-0.51	(-2.88)***	-0.06
Price Impact$_{1min}^{pass.}$	-4.67	-15.99	-3.30	3.52	-4.68	-16.35	-3.22	3.95	-4.67	-15.16	-3.35	2.94	0.01	(0.05)	0.00
Panel E: *HFT Interactions*															
Volume HFT	31.41	2.18	30.21	64.96	29.50	1.38	27.73	62.49	33.22	3.52	32.24	66.35	3.72	(10.58)***	0.19
Volume aggr. HFT	20.83	0.00	17.87	53.65	19.07	0.00	15.60	51.73	22.49	0.00	20.10	55.11	3.42	(10.61)***	0.19
	$N = 11{,}724$				$N = 5{,}704$				$N = 6{,}020$						

Table 4: Baseline Execution Cost Analysis

This table shows parent order level regressions with stock-day fixed effects in addition to quarter-hour intraday fixed effects for the beginning of the order's execution. The dependent variable is the execution cost in basis points. *Order Size* is the parent order size in Euro. *Market Trading* is the log total trading volume of all other trades during the execution of the parent order. *Buy* is a binary variable equal to one for buy orders. $Volatility_{t\text{-}10min}$ is the standard deviation of 10ms quote midpoint returns and $Return_{t\text{-}10min}$ is the trade direction signed quote midpoint return in the 10min interval before the first execution of a child order, in bps, respectively. Since the previous two variables are based on less than 10min of observations for early trades, a binary variable for trades starting before 9:10h is included in all models but not reported. *Information* is the permanent price impact as measured by the trade direction signed return from the quote midpoint immediately before the parent order to the closing quote midpoint one day after the last child order execution, in bps. *Duration* is the time difference between the first and last execution of a child order, adjusted for exchange trading hours. *Aggressiveness* is the volume of executions of marketable orders relative to the size of the parent order, in percent. *Child Order Executions* is the number of individual child order executions. *MTF* is the total volume executed on MTFs relative to the size of the parent order, in percent. The observations are weighted by the inverse probability of being in their observed category of colocation and agency, where the probabilities are estimated in a first stage using a multinomial logit model with the same independent variables while the standard errors are estimated using bootstrapping with 1,000 iterations. Standard errors are clustered by exchange member and stock. t-statistics are given in parentheses. ***, **, * denotes significance at the 1%, 5%, 10%–level, respectively.

	(1)	(2)	(3)
log Order Size	2.597***	2.663***	3.330***
	(2.63)	(2.71)	(3.21)
log Market Trading		−3.370*	−3.441*
		(−1.67)	(−1.71)
Buy	1.870	1.936	1.985
	(1.29)	(1.34)	(1.37)
$Volatility_{t\text{-}10min}$	17.310	17.035	17.081
	(1.35)	(1.33)	(1.33)
$Return_{t\text{-}10min}$	0.005	0.006	0.006
	(0.17)	(0.19)	(0.18)
Information	0.146***	0.145***	0.145***
	(27.65)	(27.57)	(27.59)
Duration	−1.675***	−1.033*	−0.975*
	(−4.72)	(−1.88)	(−1.78)
Aggressiveness	0.305***	0.305***	0.310***
	(12.32)	(12.36)	(12.45)
log Child Order Executions	4.114***	4.142***	3.280***
	(5.73)	(5.77)	(4.06)
MTF			0.065***
			(2.97)
Stock-Day FE	✓	✓	✓
Intraday FE	✓	✓	✓
Inv. Prob. Weighting	✓	✓	✓
Exchange Member FE	–	–	–
	$N = 11{,}717$		

Table 5: Exchange Member Colocation and HFT

This table shows parent order level regressions with stock-day and intraday fixed effects. The dependent variable is the execution cost in basis points. *Agency* is a binary variable equal to one for agency and zero for proprietary orders. *Colo* is a binary variable equal to one if the exchange member is colocated on the primary market or on the MTF. *HFT* is the fraction of the parent order executed against an HFT counterparty in percent. $HFT^{Aggr.}$ and $HFT^{Pass.}$ is the fraction of the parent order executed against an HFT counterparty where the HFT takes or provides liquidity, respectively, in percent. $ColoHFT^{Aggr.}$ and $ColoHFT^{Pass.}$ is the fraction of the parent order executed against a liquidity taking or providing HFT, respectively, on a venue where the exchange member is colocated, in percent. The HFT variables are centered at zero. The remaining variables are defined as in Table 4 and all included in all models. The observations are weighted by the inverse probability of being in their observed category of colocation and agency, where the probabilities are estimated in a first stage using a multinomial logit model with the same independent variables as in Table 4 while the standard errors are estimated using bootstrapping with 1,000 iterations. Standard errors are clustered by exchange member and stock. t-statistics are given in parentheses. ***, **, * denotes significance at the 1%, 5%, 10%–level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Agency	4.465***	4.365***	0.555	0.682	1.029	3.654
	(2.87)	(2.80)	(0.26)	(0.32)	(0.49)	(0.96)
Colo		−2.301	−5.978***	−5.960***	−5.659***	−5.857***
		(−1.45)	(−2.71)	(−2.71)	(−2.58)	(−2.62)
Colo×Agency			7.223**	7.165**	6.289**	6.024**
			(2.48)	(2.47)	(2.16)	(2.02)
HFT				0.088**		
				(1.97)		
$\text{HFT}^{\text{Aggr.}}$					0.365***	0.451***
					(6.65)	(5.77)
$\text{HFT}^{\text{Pass.}}$					−0.304***	−0.382***
					(−4.15)	(−3.87)
$\text{ColoHFT}^{\text{Aggr.}}$						−0.211**
						(−2.01)
$\text{ColoHFT}^{\text{Pass.}}$						0.334***
						(2.85)
Agency×$\text{HFT}^{\text{Aggr.}}$						−0.090
						(−0.88)
Agency×$\text{HFT}^{\text{Pass.}}$						−0.056
						(−0.48)
Agency×$\text{ColoHFT}^{\text{Aggr.}}$						0.254
						(1.64)
Agency×$\text{ColoHFT}^{\text{Pass.}}$						−0.189
						(−1.07)
All Baseline Controls	✓	✓	✓	✓	✓	✓
Stock-Day FE	✓	✓	✓	✓	✓	✓
Intraday FE	✓	✓	✓	✓	✓	✓
Inv. Prob. Weighting	✓	✓	✓	✓	✓	✓
Exchange Member FE	–	–	–	–	–	–
$N = 11{,}717$						

Table 6: Exchange Member Colocation and HFT with Exchange Member FE

This table shows parent order level regressions with stock-day, intraday, and additionally exchange member fixed effects. The dependent variable in all models is the execution cost in basis points. The independent variables are defined as in Table 4 and Table 5. As being colocated on the MTF does not vary within exchange members, only colocation at the stock's primary market is considered. Consequently, trading against HFTs has been split by trading venue type. The HFT variables are centered at zero. The observations are weighted by the inverse probability of being in their observed category of colocation and agency, where the probabilities are estimated in a first stage using a multinomial logit model with the same independent variables as in Table 4 while the standard errors are estimated using bootstrapping with 1,000 iterations. Standard errors are clustered by exchange member and stock. t-statistics are given in parentheses. ***, **, * denotes significance at the 1%, 5%, 10%–level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Agency	9.217***	9.215***	4.991*	5.111*	5.180*	4.529
	(4.06)	(4.06)	(1.70)	(1.74)	(1.77)	(1.52)
Colo_{PM}		−2.937	−6.258*	−6.126*	−6.182*	−6.879*
		(−0.90)	(−1.74)	(−1.70)	(−1.71)	(−1.91)
$\text{Colo}_{\text{PM}}\times$Agency			7.834**	7.763**	7.704**	7.659**
			(2.22)	(2.20)	(2.18)	(2.11)
HFT				0.091**		
				(2.10)		
$\text{HFT}^{\text{Aggr.}}$					0.351***	0.352***
					(6.34)	(4.75)
$\text{HFT}^{\text{Pass.}}$					−0.297***	−0.353***
					(−4.28)	(−3.99)
$\text{ColoHFT}^{\text{Aggr.}}_{\text{PM}}$						−0.110
						(−0.91)
$\text{ColoHFT}^{\text{Pass.}}_{\text{PM}}$						0.407***
						(2.62)
Agency$\times\text{HFT}^{\text{Aggr.}}_{\text{PM}}$						0.038
						(0.36)
Agency$\times\text{HFT}^{\text{Pass.}}_{\text{PM}}$						0.009
						(0.07)
Agency$\times\text{HFT}^{\text{Aggr.}}_{\text{MTF}}$						0.115
						(0.93)
Agency$\times\text{HFT}^{\text{Pass.}}_{\text{MTF}}$						−0.031
						(−0.21)
Agency$\times\text{ColoHFT}^{\text{Aggr.}}_{\text{PM}}$						0.021
						(0.13)
Agency$\times\text{ColoHFT}^{\text{Pass.}}_{\text{PM}}$						−0.361*
						(−1.73)
All Baseline Controls	✓	✓	✓	✓	✓	✓
Stock-Day FE	✓	✓	✓	✓	✓	✓
Intraday FE	✓	✓	✓	✓	✓	✓
Inv. Prob. Weighting	✓	✓	✓	✓	✓	✓
Exchange Member FE	✓	✓	✓	✓	✓	✓
$N = 11{,}717$						

Table 7: Order to Trade Ratios

This table shows parent order level regressions with stock-day fixed effects in addition to quarter-hour intraday fixed effects for the beginning of the order's execution. Column (2) additionally includes exchange member fixed effects. The dependent variable is the number of child order submissions relative to the number of child order executions. The independent variables are defined as in Table 4 and Table 5. The observations are weighted by the inverse probability of being in their observed category of colocation and agency, where the probabilities are estimated in a first stage using a multinomial logit model with the same independent variables as in Table 4 while the standard errors are estimated using bootstrapping with 1,000 iterations. Standard errors are clustered by exchange member and stock. t-statistics are given in parentheses. ***, **, * denotes significance at the 1%, 5%, 10%–level, respectively.

	(1)	(2)
Agency	-1.425	-0.424
	(-0.42)	(-0.16)
Colo	10.722^{**}	3.883
	(2.12)	(0.99)
Colo×Agency	-9.679^{*}	-10.481^{***}
	(-1.80)	(-2.60)
All Baseline Controls	✓	✓
Stock-Day FE	✓	✓
Intraday FE	✓	✓
Inv. Prob. Weighting	✓	✓
Exchange Member FE	–	✓
$N = 10{,}411$		

Table 8: Child-order Execution Quality

This table shows parent order level regressions with stock-day fixed effects in addition to quarter-hour intraday fixed effects for the beginning of the order's execution. Columns (2) and (4) additionally include exchange member fixed effects. Each panel shows a separate set of regression results where the dependent variables are the effective half spread and the price impact after 1 second and 1 minute, respectively. All dependent variables are parent order level averages of the respective measures across all aggressive (liquidity-taking) or passive (liquidity-providing) child order executions of a given parent order. All three measures are expressed in basis points where positive (negative) values indicate a cost (profit) for the institution. The independent variables are defined as in Table 4 and Table 5. The observations are weighted by the inverse probability of being in their observed category of colocation and agency, where the probabilities are estimated in a first stage using a multinomial logit model with the same independent variables as in Table 4 while the standard errors are estimated using bootstrapping with 1,000 iterations. Standard errors are clustered by exchange member and stock. t-statistics are given in parentheses. ***, **, * denotes significance at the 1%, 5%, 10%–level, respectively.

	(1) Aggr.	(2) Aggr.	(3) Pass.	(4) Pass.
Panel A: *Effective Half Spread*				
Agency	0.421***	0.385*	−0.009	0.261
	(3.09)	(1.92)	(−0.07)	(1.49)
Colo	−0.739***	−0.147	−0.487***	−0.302
	(−5.62)	(−0.62)	(−3.82)	(−1.40)
Colo×Agency	0.045	0.176	0.084	0.170
	(0.26)	(0.72)	(0.50)	(0.87)
Panel B: *Price Impact at 1 Second*				
Agency	0.335*	0.768***	−0.331*	0.010
	(1.67)	(2.80)	(−1.93)	(0.05)
Colo	−0.694***	0.290	−0.753***	−0.035
	(−3.80)	(0.88)	(−5.09)	(−0.15)
Colo×Agency	0.351	−0.096	0.616***	0.788***
	(1.45)	(−0.30)	(3.05)	(3.28)
Panel C: *Price Impact at 1 Minute*				
Agency	−0.091	0.390	−0.741***	0.117
	(−0.31)	(1.00)	(−2.91)	(0.38)
Colo	−1.009***	0.084	−0.853***	−0.385
	(−3.35)	(0.18)	(−3.79)	(−1.05)
Colo×Agency	0.930**	0.096	0.873***	0.517
	(2.34)	(0.19)	(2.70)	(1.38)
All Baseline Controls	✓	✓	✓	✓
Stock-Day FE	✓	✓	✓	✓
Intraday FE	✓	✓	✓	✓
Inv. Prob. Weighting	✓	✓	✓	✓
Exchange Member FE	–	✓	–	✓
	N = 10,926		N = 10,969	

Internet Appendix

In this internet appendix, we provide evidence that our key results remain robust to two adjustments in our model. First, we estimate the panel regression without employing IPW. Table A1 reports the baseline results. The coefficients for log order size, Information, parent order duration, aggressiveness, log child order executions, and MTF trading are consistent in magnitude and statistical significance with the main specification employing IPW. Additionally, the market trading variable that is weakly significant in the main specification becomes insignificant in the estimation without IPW. Finally, the trade direction variable and historical volatility become weakly significant in the specification without IPW. Table A2 reports the relationship between execution costs on the one hand and trading capacity, colocation, and HFT interactions on the other hand. Again, the results remain very similar to the estimations with IPW. After controlling for the baseline variables, agency orders have a higher execution cost than proprietary orders, colocated proprietary orders have lower execution costs than colocated agency orders, and aggressive (passive) HFT activity is positively (negatively) associated with order execution costs. The sign, magnitude, and statistical significance of the coefficients is also similar between the two specifications.

Table A3 contains the results after including exchange-member fixed effects. While the overall conclusions remain unchanged we do observe some differences compared to the IPW results. Specifically, the execution costs of agency orders while higher are weakly significant after controlling for colocation and HFT. At the same time, the coefficient of the colocation dummy and its interaction with the agency dummy in specifications (3) to (6) is larger in absolute terms and statistically significant. Finally, the relationship between execution costs and total HFT as well as its decomposition into aggressive and passive strategies remain largely unchanged. Finally, Figure A1 shows that the broker-level difference in fixed effects between agency and proprietary orders is similar to the output with IPW. Overall, the above findings indicate that our key results are robust to the weighting scheme employed in the estimation process.

Next, we estimate all the main results by computing execution costs after including exchange fees and subtracting any rebates. For exchanges offering fee schedules dependent on the members' total trading volume, we assume the fee/rebate corresponding to the highest volume threshold. As some of the competing MTFs operate a maker-taker fee structure, offering rebates to liquidity providers, the sum of fees incurred can be zero or even negative in some cases. We report the coefficients from the estimation with and without IPW. The results are reported in Table A4, Table A5, and Table A6. While we do observe small differences in the statistical significance of some coefficients, the overall conclusions concerning the relationship between execution costs and trader capacity, colocation, and HFT remain robust to including fees/rebates.

Figure A1: Difference between Agency and Proprietary Trades of Colocated Exchange Members without IPW

This graph shows the distribution of within-exchange member differences in execution costs in bps between agency and proprietary trades that a given exchange member executes on a trading venue where they are colocated. The estimates are based on regressions that include exchange member-capacity-colocation fixed effects in addition to baseline control variables and stock-day and intraday fixed effects. Standard errors are clustered by exchange member and stock. The ranges indicate 90% confidence intervals.

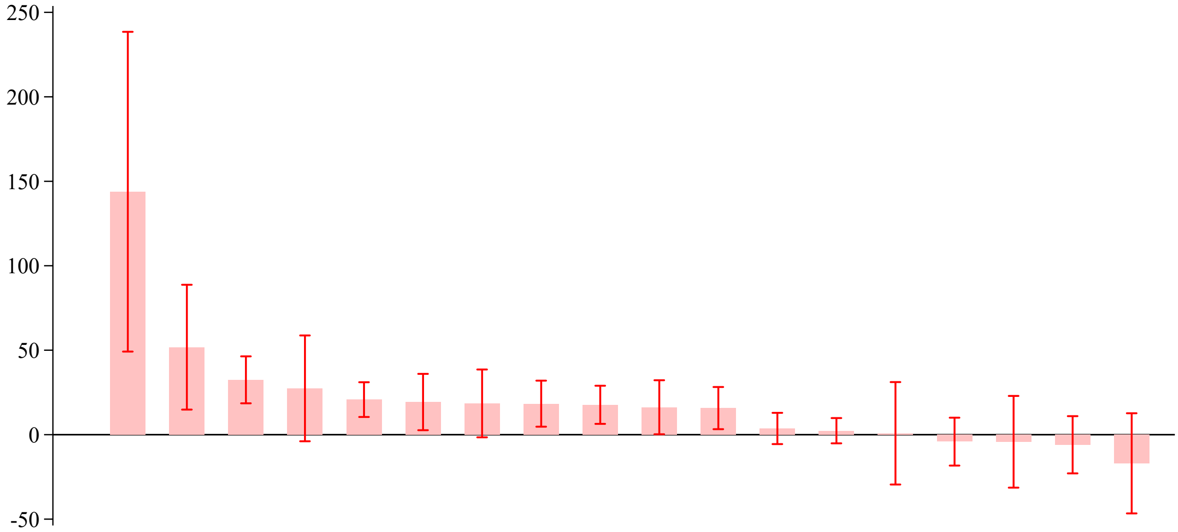

Table A1: Baseline Execution Cost Analysis without IPW

This table shows parent order level regressions with stock-day fixed effects in addition to quarter-hour intraday fixed effects for the beginning of the order's execution. The dependent variable is the execution cost in basis points. *Order Size* is the parent order size in Euro. *Market Trading* is the log total trading volume of all other trades during the execution of the parent order. *Buy* is a binary variable equal to one for buy orders. *Volatility* $_{t\text{-}10min}$ is the standard deviation of 10ms quote midpoint returns and *Return* $_{t\text{-}10min}$ is the trade direction signed quote midpoint return in the 10min interval before the first execution of a child order, in bps, respectively. Since the previous two variables are based on less than 10min of observations for early trades, a binary variable for trades starting before 9:10h is included in all models but not reported. *Information* is the permanent price impact as measured by the trade direction signed return from the quote midpoint immediately before the parent order to the closing quote midpoint one day after the last child order execution, in bps. *Duration* is the time difference between the first and last execution of a child order, adjusted for exchange trading hours. *Aggressiveness* is the volume of executions of marketable orders relative to the size of the parent order, in percent. *Child Order Executions* is the number of individual child order executions. *MTF* is the total volume executed on MTFs relative to the size of the parent order, in percent. Standard errors are clustered by exchange member and stock. t-statistics are given in parentheses. ***, **, * denotes significance at the 1%, 5%, 10%–level, respectively.

	(1)	(2)	(3)
log Order Size	2.646***	2.671***	3.379***
	(2.90)	(2.92)	(3.56)
log Market Trading		−1.226	−1.280
		(−0.61)	(−0.64)
Buy	2.133*	2.140*	2.173*
	(1.68)	(1.69)	(1.71)
Volatility $_{\text{t-10min}}$	19.553*	19.645*	19.733*
	(1.77)	(1.78)	(1.78)
Return $_{\text{t-10min}}$	0.000	0.000	0.000
	(0.00)	(0.00)	(−0.01)
Information	0.142***	0.142***	0.142***
	(31.40)	(31.39)	(31.37)
Duration	−1.304***	−1.065**	−1.001*
	(−4.18)	(−2.03)	(−1.91)
Aggressiveness	0.305***	0.305***	0.309***
	(14.11)	(14.10)	(14.28)
log Child Order Executions	4.238***	4.243***	3.396***
	(6.25)	(6.26)	(4.58)
MTF			0.060***
			(3.12)
Stock-Day FE	✓	✓	✓
Intraday FE	✓	✓	✓
Inv. Prob. Weighting	–	–	–
Exchange Member FE	–	–	–
	$N = 11{,}717$		

Table A2: Exchange Member Colocation and HFT without IPW

This table shows parent order level regressions with stock-day and intraday fixed effects. The dependent variable is the execution cost in basis points. *Agency* is a binary variable equal to one for agency and zero for proprietary orders. *Colo* is a binary variable equal to one if the exchange member is colocated on the primary market or on the MTF. *HFT* is the fraction of the parent order executed against an HFT counterparty in percent. $HFT^{Aggr.}$ and $HFT^{Pass.}$ is the fraction of the parent order executed against an HFT counterparty where the HFT takes or provides liquidity, respectively, in percent. $ColoHFT^{Aggr.}$ and $ColoHFT^{Pass.}$ is the fraction of the parent order executed against a liquidity taking or providing HFT, respectively, on a venue where the exchange member is colocated, in percent. The HFT variables are centered at zero. The remaining variables are defined as in Table 4 and all included in all models. Standard errors are clustered by exchange member and stock. t-statistics are given in parentheses. ***, **, * denotes significance at the 1%, 5%, 10%–level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Agency	4.593***	4.477***	−0.304	−0.234	0.377	3.765
	(3.07)	(2.98)	(−0.15)	(−0.11)	(0.18)	(1.08)
Colo		−1.840	−6.212***	−6.195***	−5.819***	−5.309***
		(−1.29)	(−3.11)	(−3.11)	(−2.94)	(−2.70)
Colo×Agency			8.840***	8.826***	7.793***	7.085**
			(3.21)	(3.21)	(2.83)	(2.55)
HFT				0.081**		
				(2.09)		
$HFT^{Aggr.}$					0.347***	0.468***
					(7.02)	(6.54)
$HFT^{Pass.}$					−0.296***	−0.334***
					(−4.70)	(−3.72)
$ColoHFT^{Aggr.}$						−0.258***
						(−2.72)
$ColoHFT^{Pass.}$						0.280***
						(2.63)
Agency×$HFT^{Aggr.}$						−0.122
						(−1.33)
Agency×$HFT^{Pass.}$						−0.044
						(−0.41)
Agency×$ColoHFT^{Aggr.}$						0.244*
						(1.68)
Agency×$ColoHFT^{Pass.}$						−0.224
						(−1.36)
All Baseline Controls	✓	✓	✓	✓	✓	✓
Stock-Day FE	✓	✓	✓	✓	✓	✓
Intraday FE	✓	✓	✓	✓	✓	✓
Inv. Prob. Weighting	–	–	–	–	–	–
Exchange Member FE	–	–	–	–	–	–
$N = 11{,}717$						

Table A3: Exchange Member Colocation and HFT with Exchange Member FE without IPW

This table shows parent order level regressions with stock-day, intraday, and additionally exchange member fixed effects. The dependent variable in all models is the execution cost in basis points. The independent variables are defined as in Table 4 and Table 5. As being colocated on the MTF does not vary within exchange members, only colocation at the stock's primary market is considered. Consequently, trading against HFTs has been split by trading venue type. The HFT variables are centered at zero. Standard errors are clustered by exchange member and stock. t-statistics are given in parentheses. ***, **, * denotes significance at the 1%, 5%, 10%–level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Agency	8.668***	8.543***	3.607	3.756	3.843	3.489
	(4.12)	(4.06)	(1.37)	(1.43)	(1.46)	(1.30)
Colo $_{PM}$		−4.806	−8.305***	−8.150**	−8.259***	−8.417***
		(−1.63)	(−2.60)	(−2.55)	(−2.59)	(−2.64)
Colo $_{PM}$ × Agency			8.865***	8.764***	8.674***	8.515**
			(2.66)	(2.63)	(2.60)	(2.48)
HFT				0.095**		
				(2.44)		
HFT $^{Aggr.}$					0.343***	0.362***
					(6.93)	(5.28)
HFT $^{Pass.}$					−0.274***	−0.274***
					(−4.39)	(−3.20)
ColoHFT $^{Aggr.}_{PM}$						−0.123
						(−1.14)
ColoHFT $^{Pass.}_{PM}$						0.219
						(1.55)
Agency × HFT $^{Aggr.}_{PM}$						−0.026
						(−0.28)
Agency × HFT $^{Pass.}_{PM}$						−0.025
						(−0.22)
Agency × HFT $^{Aggr.}_{MTF}$						0.088
						(0.75)
Agency × HFT $^{Pass.}_{MTF}$						−0.047
						(−0.33)
Agency × ColoHFT $^{Aggr.}_{PM}$						0.133
						(0.82)
Agency × ColoHFT $^{Pass.}_{PM}$						−0.231
						(−1.15)
All Baseline Controls	✓	✓	✓	✓	✓	✓
Stock-Day FE	✓	✓	✓	✓	✓	✓
Intraday FE	✓	✓	✓	✓	✓	✓
Inv. Prob. Weighting	–	–	–	–	–	–
Exchange Member FE	✓	✓	✓	✓	✓	✓
			$N = 11{,}717$			

Table A4: Baseline Execution Cost Analysis after Exchange Fees

This table shows parent order level regressions with stock-day fixed effects in addition to quarter-hour intraday fixed effects for the beginning of the order's execution. The dependent variable is the execution cost after adding exchange fees and subtracting rebates in basis points. *Order Size* is the parent order size in Euro. *Market Trading* is the log total trading volume of all other trades during the execution of the parent order. *Buy* is a binary variable equal to one for buy orders. $Volatility_{t\text{-}10min}$ is the standard deviation of 10ms quote midpoint returns and $Return_{t\text{-}10min}$ is the trade direction signed quote midpoint return in the 10min interval before the first execution of a child order, in bps, respectively. Since the previous two variables are based on less than 10min of observations for early trades, a binary variable for trades starting before 9:10h is included in all models but not reported. *Information* is the permanent price impact as measured by the trade direction signed return from the quote midpoint immediately before the parent order to the closing quote midpoint one day after the last child order execution, in bps. *Duration* is the time difference between the first and last execution of a child order, adjusted for exchange trading hours. *Aggressiveness* is the volume of executions of marketable orders relative to the size of the parent order, in percent. *Child Order Executions* is the number of individual child order executions. *MTF* is the total volume executed on MTFs relative to the size of the parent order, in percent. The observations are weighted by the inverse probability of being in their observed category of colocation and agency, where the probabilities are estimated in a first stage using a multinomial logit model with the same independent variables while the standard errors are estimated using bootstrapping with 1,000 iterations. Standard errors are clustered by exchange member and stock. t-statistics are given in parentheses. ***, **, * denotes significance at the 1%, 5%, 10%–level, respectively.

	(1)	(2)	(3)
log Order Size	2.281**	2.378**	2.975***
	(2.25)	(2.36)	(2.79)
log Market Trading		−4.906**	−4.970**
		(−2.27)	(−2.30)
Buy	1.925	2.021	2.064
	(1.30)	(1.37)	(1.40)
$Volatility_{t\text{-}10min}$	15.370	14.968	15.010
	(1.10)	(1.07)	(1.07)
$Return_{t\text{-}10min}$	0.002	0.003	0.002
	(0.04)	(0.07)	(0.07)
Information	0.154***	0.154***	0.154***
	(25.15)	(25.13)	(25.13)
Duration	−1.857***	−0.922	−0.870
	(−4.92)	(−1.58)	(−1.49)
Aggressiveness	0.303***	0.304***	0.309***
	(11.94)	(12.00)	(12.06)
log Child Order Executions	4.261***	4.302***	3.530***
	(5.77)	(5.83)	(4.23)
MTF			0.059***
			(2.59)
Stock-Day FE	✓	✓	✓
Intraday FE	✓	✓	✓
Inv. Prob. Weighting	✓	✓	✓
Exchange Member FE	–	–	–
	$N = 11{,}724$		

Table A5: Exchange Member Colocation and HFT after Exchange Fees

This table shows parent order level regressions with stock-day and intraday fixed effects. The dependent variable is the execution cost after adding exchange fees and subtracting rebates in basis points. *Agency* is a binary variable equal to one for agency and zero for proprietary orders. *Colo* is a binary variable equal to one if the exchange member is colocated on the primary market or on the MTF. *HFT* is the fraction of the parent order executed against an HFT counterparty in percent. $HFT^{Aggr.}$ and $HFT^{Pass.}$ is the fraction of the parent order executed against an HFT counterparty where the HFT takes or provides liquidity, respectively, in percent. $ColoHFT^{Aggr.}$ and $ColoHFT^{Pass.}$ is the fraction of the parent order executed against a liquidity taking or providing HFT, respectively, on a venue where the exchange member is colocated, in percent. The HFT variables are centered at zero. The remaining variables are defined as in Table 4 and all included in all models. The observations are weighted by the inverse probability of being in their observed category of colocation and agency, where the probabilities are estimated in a first stage using a multinomial logit model with the same independent variables as in Table 4 while the standard errors are estimated using bootstrapping with 1,000 iterations. Standard errors are clustered by exchange member and stock. t-statistics are given in parentheses. ***, **, * denotes significance at the 1%, 5%, 10%–level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Agency	4.600***	4.496***	0.578	0.692	1.044	4.081
	(2.88)	(2.81)	(0.27)	(0.32)	(0.48)	(1.02)
Colo		−2.420	−6.200***	−6.184***	−5.879**	−6.124***
		(−1.48)	(−2.70)	(−2.69)	(−2.57)	(−2.61)
Colo×Agency			7.426**	7.375**	6.485**	6.209**
			(2.45)	(2.44)	(2.14)	(1.99)
HFT				0.079*		
				(1.73)		
$\text{HFT}^{\text{Aggr.}}$					0.360***	0.448***
					(6.47)	(5.65)
$\text{HFT}^{\text{Pass.}}$					−0.319***	−0.400***
					(−4.25)	(−3.95)
$\text{ColoHFT}^{\text{Aggr.}}$						−0.202*
						(−1.87)
$\text{ColoHFT}^{\text{Pass.}}$						0.351***
						(2.88)
$\text{Agency}\times\text{HFT}^{\text{Aggr.}}$						−0.104
						(−0.99)
$\text{Agency}\times\text{HFT}^{\text{Pass.}}$						−0.067
						(−0.55)
$\text{Agency}\times\text{ColoHFT}^{\text{Aggr.}}$						0.260
						(1.64)
$\text{Agency}\times\text{ColoHFT}^{\text{Pass.}}$						−0.189
						(−1.04)
All Baseline Controls	✓	✓	✓	✓	✓	✓
Stock-Day FE	✓	✓	✓	✓	✓	✓
Intraday FE	✓	✓	✓	✓	✓	✓
Inv. Prob. Weighting	✓	✓	✓	✓	✓	✓
Exchange Member FE	–	–	–	–	–	–
$N = 11{,}724$						

Table A6: Exchange Member Colocation and HFT with Exchange Member FE after Exchange Fees

This table shows parent order level regressions with stock-day, intraday, and additionally exchange member fixed effects. The dependent variable is the execution cost after adding exchange fees and subtracting rebates in basis points. The independent variables are defined as in Table 4 and Table 5. As being colocated on the MTF does not vary within exchange members, only colocation at the stock's primary market is considered. Consequently, trading against HFTs has been split by trading venue type. The HFT variables are centered at zero. The observations are weighted by the inverse probability of being in their observed category of colocation and agency, where the probabilities are estimated in a first stage using a multinomial logit model with the same independent variables as in Table 4 while the standard errors are estimated using bootstrapping with 1,000 iterations. Standard errors are clustered by exchange member and stock. t-statistics are given in parentheses. ***, **, * denotes significance at the 1%, 5%, 10%–level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Agency	9.234***	9.232***	4.378	4.486	4.555	3.988
	(3.99)	(3.98)	(1.45)	(1.48)	(1.51)	(1.30)
Colo_{PM}		−3.296	−7.112*	−6.993*	−7.051*	−7.689**
		(−0.99)	(−1.91)	(−1.88)	(−1.89)	(−2.06)
$\text{Colo}_{\text{PM}} \times \text{Agency}$			9.002**	8.938**	8.878**	8.742**
			(2.45)	(2.43)	(2.41)	(2.31)
HFT				0.082*		
				(1.84)		
$\text{HFT}^{\text{Aggr.}}$					0.348***	0.356***
					(6.18)	(4.72)
$\text{HFT}^{\text{Pass.}}$					−0.316***	−0.366***
					(−4.42)	(−4.00)
$\text{ColoHFT}^{\text{Aggr.}}_{\text{PM}}$						−0.108
						(−0.87)
$\text{ColoHFT}^{\text{Pass.}}_{\text{PM}}$						0.416***
						(2.60)
$\text{Agency} \times \text{HFT}^{\text{Aggr.}}_{\text{PM}}$						0.011
						(0.10)
$\text{Agency} \times \text{HFT}^{\text{Pass.}}_{\text{PM}}$						−0.021
						(−0.16)
$\text{Agency} \times \text{HFT}^{\text{Aggr.}}_{\text{MTF}}$						0.100
						(0.79)
$\text{Agency} \times \text{HFT}^{\text{Pass.}}_{\text{MTF}}$						−0.033
						(−0.22)
$\text{Agency} \times \text{ColoHFT}^{\text{Aggr.}}_{\text{PM}}$						0.052
						(0.30)
$\text{Agency} \times \text{ColoHFT}^{\text{Pass.}}_{\text{PM}}$						−0.350
						(−1.63)
All Baseline Controls	✓	✓	✓	✓	✓	✓
Stock-Day FE	✓	✓	✓	✓	✓	✓
Intraday FE	✓	✓	✓	✓	✓	✓
Inv. Prob. Weighting	✓	✓	✓	✓	✓	✓
Exchange Member FE	✓	✓	✓	✓	✓	✓
$N = 11{,}724$						

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