

Retail Order Flow Segmentation, Price Improvements, and Market Quality: Evidence from Xetra Retail

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Abstract

Exchanges worldwide are introducing on-exchange retail programs that segment retail order flow within lit markets and compete with off-exchange internalization and payment-for-order-flow models. Despite their rapid adoption, little causal evidence exists on whether such mechanisms can improve retail execution without harming market quality. We study the introduction of the Xetra Retail Service (XR), which enables retail orders to interact with competing Retail Liquidity Providers (RLPs). Retail orders are executed against RLPs that offer price improvements over displayed quotes or in the regular limit order book. We use granular ETF trading data in a difference-in-differences design (control: Euronext Milan) to assess execution outcomes and market quality effects. We find that 63% of retail ETF trades receive price improvement, averaging 0.93 bps (1.35 bps conditional). As expected, improvements are larger when spreads are wider and volatility is higher. Unexpectedly, price improvements are more likely for larger orders. At the overall market quality level, spreads, activity, and volatility remain stable, though displayed depth declines modestly. Overall, on-exchange retail segmentation can enhance retail execution without impairing market quality.

Keywords: Retail Trading, Market Segmentation, Adverse Selection, Retail Liquidity Provider, Exchange Traded Funds

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1. Introduction

Advances in trading technology and evolving regulation have spurred the development of mechanisms that segment retail orders from institutional flow, most prominently through payment for order flow (PFOF) and internalization arrangements. These practices allow brokers to route retail orders to specific trading venues or counterparties in exchange for monetary benefits. Proponents argue that retail order flow segmentation lowers transaction costs and improves execution quality through reduced commissions and potential price improvements. Critics, however, warn that segmentation fragments liquidity and may impair market quality by siphoning uninformed retail orders away from public exchanges that are then dominated by informed traders as the relative share of informed trading increases due to retail segmentation.

This tension has fueled intense academic and regulatory scrutiny. In the United States, concerns about internalization and PFOF have prompted SEC proposals to reform retail execution practices (SEC, 2022). In the European Union, the upcoming 2026 ban on PFOF (ESMA, 2024) underscores similar concerns about fairness and transparency. Yet, despite the centrality of retail trading in these policy debates, empirical evidence on how on-exchange retail segmentation affects execution quality and overall market performance remains limited.

At the same time, exchanges worldwide are increasingly adopting on-exchange retail segmentation mechanisms. A growing number of venues now offer programs that isolate retail order flow and match it against dedicated liquidity providers within the exchange environment. In the U.S., five major exchanges, including Nasdaq, NYSE, NYSE Arca, IEX, and Cboe, operate Retail Liquidity Programs (Ernst et al., 2024). In Europe, Euronext launched its Best of Book mechanism in 2016, followed by Deutsche Börse’s introduction of Xetra Retail Service (XR) in 2024. This shift is further accelerated in Europe by the forthcoming ban on PFOF under the MiFID II review, which strengthens the incentives to develop on-exchange solutions for retail execution. Despite this rapid institutional evolution, academic research on on-exchange retail segmentation remains nascent, with only limited studies on the NYSE RLP program (Jain et al., 2021; Garriott and Walton, 2018) and an industry analysis of Euronext Best of Book (Besson and Comp  rot, 2020). This stands in stark contrast to the extensive literature on off-exchange segmentation, whether via dark pools (e.g., Zhu, 2014) or PFOF-based retail wholesalers or venues (e.g., Brown et al., 2024; Baldauf et al., 2024). As a result, little is known about whether exchange-integrated retail mechanisms can deliver execution quality benefits while preserving market quality on the primary order book.

The German securities market offers a unique setting to examine these issues. In May 2024, Deutsche B  rse introduced XR, a functionality designed to provide retail investors with enhanced execution quality directly within the exchange’s infrastructure. In March 2025, XR was expanded to exchange-traded funds (ETFs) (Deutsche B  rse Group, 2025c). Unlike off-exchange internalizers, XR integrates retail orders into the central limit order book (CLOB) but allows dedicated Retail Liquidity Providers (RLPs) to compete for retail order flow by offering price improvements relative to displayed CLOB quotes. To incentivize participation, XR employs

differentiated fee schedules, i.e., reduced fees for retail-routing brokers and higher fees for RLPs seeking access to relatively retail flow. This design combines the efficiency of on-exchange trading with the tailored execution benefits of segmented retail programs, creating an ideal environment to assess whether on-exchange segmentation can deliver price improvements without adversely affecting overall market quality.

This paper focuses on ETFs, which are among the most actively traded instruments by retail investors due to their low cost, transparency, and diversification. Despite ETFs' growing prominence, empirical work on the impact of retail order flow segmentation on ETF execution quality is scarce. Understanding how retail-oriented mechanisms affect ETF trading is important not only for assessing investor outcomes but also for evaluating market fairness and efficiency in one of the most liquid asset classes.

By analyzing more than 180,000 ETF trades executed against RLPs via XR, we address three interrelated research questions. First, we assess the extent and magnitude of price improvements achieved by ETF orders executed via XR relative to the best available CLOB quotes. Second, we examine the structural determinants of these price improvements, focusing on how order and market conditions shape the likelihood and economic size of enhancements in execution quality. Third, we analyze the broader market quality implications of the XR introduction, measuring its impact on liquidity, volatility, and trading activity using a difference-in-differences (DiD) framework that exploits a matched control group of identical ETFs traded on Euronext Milan (formerly Borsa Italiana).

Our empirical analysis yields three main findings. First, ETFs executed via XR achieve meaningful and widespread price improvements. Nearly 63% of all retail trades receive executions at prices better than the prevailing top-of-book quotes, with an average improvement of 0.93 basis points across all trades (1.35 basis points conditional on receiving an improvement). These benefits are economically significant and persist across ETF liquidity tiers, suggesting that XR systematically enhances execution quality for retail investors. Second, the determinants of price improvements are consistent with market microstructure theory. Wider spreads increase both the probability and magnitude of improvements, while buy orders (that are more frequent than sell orders) are less likely to receive price improvements. Similarly, volatility, current order book imbalance, and quoted depth in the order book shape likelihood and magnitude of price improvements. These patterns reflect strategic RLP behavior under varying market conditions and confirm that improvements are not randomly distributed but structurally determined. Third, the market quality analysis shows no material deterioration in liquidity or other dimensions of market quality following XR's introduction. Relative quoted spreads, trading activity, order-book imbalance, and intraday volatility remain statistically unchanged, while quoted depth declines modestly. The absence of adverse outcomes implies that on-exchange retail segmentation can coexist with stable market quality, in contrast to concerns often raised about off-exchange internalization (e.g., [Weaver, 2014](#); [Zhu, 2014](#)).

This study makes three primary contributions. First, it provides the first empirical evidence on price improvements for retail ETF trading within an on-exchange retail functionality. While prior work has focused on PFOF arrangements (e.g., [Elsas et al.](#),

2022; Meyer et al., 2025) or off-exchange retail programs (e.g., Garriott and Walton, 2018; Jain et al., 2021), our setting captures a hybrid design that embeds retail flow directly into the exchange’s CLOB. Second, we contribute to the literature on execution quality and retail market design by identifying the market and order-level determinants of price improvements under an integrated exchange model, extending earlier findings for Euronext’s Best of Book (Besson and Comp  rot, 2020) and NYSE’s Retail Liquidity Program (Jain et al., 2021; Garriott and Walton, 2018). Third, we provide new evidence on the market quality implications of retail segmentation, using an identification strategy that exploits a natural experiment in the European ETF market. Together, these results inform current regulatory debates over retail trading reforms and the appropriate balance between investor protection and market efficiency.

Taken together, our findings indicate that XR successfully enhances execution quality for retail investors without impairing overall market functioning. In contrast to the segmentation concerns often associated with off-exchange internalization, XR’s on-exchange integration appears to preserve transparency and market quality while delivering meaningful price improvements. These insights contribute to the ongoing policy discussion on how to structure retail trading in light of the EU’s forthcoming PFOF prohibition and the global trend toward more segmented, investor-specific market mechanisms.

The remainder of the paper proceeds as follows. Section 2 presents related literature. Section 3 provides background on the institutional setting of XR. Section 4 presents the data and empirical design for analyzing execution quality and price improvements. Section 5 examines market quality effects using a difference-in-differences framework. Section 6 concludes.

2. Related Literature

This paper builds on three strands of literature: (i) the evolution and impact of retail trading, (ii) the effects of order flow segmentation on market quality, and (iii) execution quality and price improvements in retail trading mechanisms. Together, these studies provide the theoretical and empirical foundation for understanding the role of retail segmentation in modern market design.

2.1. *Evolution and Impact of Retail Trading*

Retail investors have become an increasingly relevant force in securities markets, accounting for roughly one-fifth of U.S. trading volume and an expanding share of European trading activity (Dyhrberg et al., 2025; Hoffmann and Jank, 2024). The United States relies heavily on internalization and payment for order flow (PFOF), while Europe’s regulatory landscape remains fragmented. Some jurisdictions, such as France and the Netherlands, prohibit PFOF entirely, whereas others, including Germany, still permit it under MiFID II’s best execution framework. The forthcoming EU-wide ban on PFOF in 2026 will thus mark a structural shift in the treatment of retail order flow.

Within Germany, retail participation has nearly doubled in recent years, and execution remains concentrated in specialized retail venues having PFOF arrangements such as Tradegate and Lang & Schwarz Exchange, which operate on single-dealer models (BaFin, 2022; Aramian and Comerton-Forde, 2023). Against this backdrop, Xetra’s introduction of XR provides an alternative model for retail execution within the public limit order book.

Classical microstructure models view retail traders as liquidity-motivated and largely uninformed (Black, 1986; Subrahmanyam, 1997), implying that their segregation may affect adverse selection and liquidity dynamics. Empirical studies confirm that retail order flow tends to be contrarian and correlated (Barber and Odean, 2008; Barber et al., 2009) but also show that it can contribute to price discovery. Kaniel et al. (2008) and Kelley and Tetlock (2013, 2017) find that retail trading predicts short-term returns, suggesting that retail investors supply liquidity to institutional traders and temporarily move prices toward fundamentals.

The pandemic-era surge in retail activity provided a natural stress test for these mechanisms. Studies such as Baig et al. (2023), Chiah and Zhong (2020), Ozik et al. (2021) show that retail trading can both enhance liquidity and increase volatility, depending on market conditions. Similarly, Foucault et al. (2011) demonstrate that reducing speculative retail trading lowers volatility, consistent with noise-trading models.

Evidence from ETF markets is more limited but growing. Bhattacharya et al. (2017) and Gempesaw et al. (2024) show that retail ETF investors often trade actively and exhibit timing mistakes, yet they remain important providers of liquidity, particularly in complex ETF products. This literature highlights the need to understand how retail participation in ETFs interacts with market structure.

2.2. Order Flow Segmentation and Market Quality

A central issue in modern market design is how order flow segmentation through dark pools, internalization, PFOF, or retail liquidity programs affects overall market quality. Fragmentation can enhance efficiency by fostering competition among venues (O’Hara and Ye, 2011; Gresse, 2017), but segmentation based on trader type may generate adverse selection externalities. Theoretical models such as Hendershott and Mendelson (2000) and Zhu (2014) show that diverting uninformed order flow from public exchanges can widen spreads and impair price discovery for remaining participants.

Empirical evidence on internalization and PFOF is mixed. Grammig and Theissen (2012) find that internalized trades on Xetra BEST, an abandoned predecessor of XR, face lower adverse selection but reduce liquidity in the main book, consistent with cream-skimming effects (Easley et al., 1996). Weaver (2014) similarly documents deteriorating market quality with higher internalization in U.S. data. In contrast, more recent studies highlight potential welfare gains. Baldauf et al. (2024) model how segmentation can improve dealers’ inventory management and reduce overall trading costs, while Elsas et al. (2022) find no measurable change in Xetra’s liquidity when a large zero-commission broker temporarily routed its orders to the main exchange instead of a PFOF venue.

Within this debate, retail liquidity programs by exchanges, such as NYSE’s Retail Liquidity Program (Garriott and Walton, 2018) and Euronext’s Best of Book (Besson and Comp  rot, 2020), represent an exchange-integrated alternative. These programs allow designated liquidity providers to offer price improvements to retail orders while retaining trades on the exchange. Both studies find moderate but significant enhancements in execution quality and modest improvements in market liquidity, suggesting that on-exchange segmentation may allow improvements for retail investors while maintaining market quality and transparency.

2.3. Execution Quality and Price Improvements

Execution quality has been studied extensively in contexts such as dark pools, internalizers, and PFOF arrangements. Brolley (2020) and Ye (2011) show theoretically that price improvements attract uninformed investors to dark venues, compensating for slower or uncertain executions. Empirically, Comerton-Forde et al. (2018) and Foley and Putni   (2016) find that Canada’s “trade-at” rule increased dark-pool price improvements but also reduced retail dark activity, implying that regulation reshapes both venue choice and execution outcomes.

In internalization settings, Menkveld et al. (2017) and Grammig and Theissen (2012) find that price improvements exist but are limited relative to the rents captured by internalizers. Aramian and Nord  n (2024) show that single-dealer platforms acting as systematic internalizers often undercut the exchange bid–ask spread, especially when the spread is wide and the tick size is not binding, due to their ability to avoid trading with informed investors.

PFOF studies consistently document positive but heterogeneous price improvements. In the U.S., Battalio and Jennings (2023), Dyhrberg et al. (2025), and Brown et al. (2024) report that wholesalers deliver measurable improvements over NBBO quotes, particularly for low-priced or illiquid stocks. Yet, execution quality varies substantially across brokers and wholesalers (Levy, 2022; Huang et al., 2024), reflecting market concentration and agency frictions. In Germany, Meyer et al. (2025) find that 99% of retail trades via the zero-commission broker Trade Republic execute at or better than Xetra prices, though ETFs exhibit smaller average improvements than stocks.

Finally, research on on-exchange retail programs is still nascent. Jain et al. (2021) show that NYSE’s program achieves consistent sub-penny price improvements, especially when tick-size constraints bind. Garriott and Walton (2018) adds that even those stocks with substantial activity in NYSE’s retail liquidity program experience no material changes in liquidity. In an industry study, Besson and Comp  rot (2020) find that Euronext’s Best of Book delivers superior net prices compared with Equiduct’s PFOF-based model, particularly in markets with wide spreads or high volatility. These findings suggest that competitive, exchange-based mechanisms can deliver meaningful retail benefits without undermining liquidity—a question directly addressed in this paper through the Xetra Retail Service.

This paper contributes to the literature in three ways. First, it provides the first analysis of an on-exchange retail segmentation mechanism for ETFs, a rapidly growing but under-studied asset class. Second, it extends research on execution quality by

quantifying both the frequency and determinants of price improvements in an on-exchange retail segmentation mechanism. Third, it evaluates the broader market quality effects of such segmentation using a difference-in-differences framework.

3. Institutional Background

Deutsche Börse’s electronic trading venue Xetra is the primary exchange in Germany and one of Europe’s most liquid markets for ETFs. Since launching its ETF segment in April 2000, Xetra has become the dominant European venue for ETF trading, accounting for roughly 28% of total pan-European volume (Deutsche Börse Group, 2025e). As of May 2025, more than 2,400 ETFs are listed on the platform, with over 60% of trading volume originating from international investors (Deutsche Börse Group, 2025b,d). Continuous trading operates between 9:00 and 17:30 CET, supported by designated sponsors who are obligated to maintain firm two-sided quotes. Order execution follows strict price–time priority within an anonymous CLOB, complemented by opening, intraday, and closing auctions.

To compete with specialized retail trading venues with single market maker models and in light of the PFOF ban in Europe from mid 2026 onwards, Deutsche Börse launched XR on May 20, 2024. XR was created to improve execution conditions for retail investors while preserving on-exchange transparency and liquidity. Initially limited to equities, the program was extended to ETFs on March 3, 2025 (Deutsche Börse Group, 2025a).¹

XR operates as a retail-focused execution framework embedded within the main Xetra infrastructure. Its design segments retail order flow from the remaining, primarily institutional order flow without diverting it to off-exchange venues. Retail orders flagged by participating brokers (Retail Member Organizations (RMOs))², remain fully integrated into the exchange’s order book and can interact both with regular CLOB orders and with dedicated RLP quotes. RLPs are specialized market participants that agree to provide liquidity to retail orders in exchange for access to this order flow. RMOs benefit from lower transaction fees when submitting eligible retail orders, while RLPs pay higher fees but gain the opportunity to trade against profitable retail flow.

Two features distinguish XR from traditional off-exchange retail trading mechanisms such as PFOF or internalization. First, XR operates fully on-exchange and is seamlessly integrated into Xetra’s CLOB. Retail brokers route orders to Xetra as usual, and the matching engine determines whether execution occurs against an RLP

¹On March 3, 2025, XR was first introduced for the 256 most traded ETFs and then extended to all tradable assets on June 1, 2025.

²Brokers serving retail clients are incentivized to register as RMOs and to flag their retail order flow accordingly, as Deutsche Börse provides substantial fee rebates for such activity. Under the current fee model, RMOs receive a 16.6% discount on transaction fees for self-directed retail orders (i.e., orders where the client instructs the broker to route the order to Xetra) and a 100% rebate for broker-directed orders routed to Xetra to achieve best execution. The latter category also includes orders submitted via smart order routers (see <https://www.xetra.com/resource/blob/4479062/c77ca2ae9614050506f995daa69a9774/data/xetra-retail-services-extension.pdf>).

quote or standing CLOB orders. This structure ensures that retail orders remain within the transparent and regulated exchange environment. Second, XR promotes competition by allowing multiple RLPs to provide liquidity for each instrument and by maintaining direct competition between RLPs and regular CLOB participants. RLPs may execute only against retail flow, and their quotes are matched only if they offer a better price than the standing orders in the CLOB or if their price is identical but the RLP quote is older and has time priority. Otherwise, or if the size of the incoming retail order is larger than that of eligible RLP quotes, the order is executed in the regular CLOB. This structure fosters competition to deliver price improvements for retail investors while preserving the integrity and transparency of the main order book.

RLP quotes are not displayed in the public CLOB but are disseminated through a dedicated data feed. All executions resulting from interactions with RLPs are published in real time as regular Xetra trades, accompanied by a specific identifier. XR is only available during continuous trading and RLP quotes are automatically removed at the start of auction phases. Standard market safeguards, including volatility interruptions and price collars, apply equally to retail and non-retail orders.

The XR architecture thus represents a hybrid form of retail order flow segmentation. It retains the advantages of centralized price discovery and transparency while introducing competitive incentives for liquidity providers to offer better execution to retail investors. This design stands in contrast to U.S.-style internalization or European PFOF models, where retail orders are often executed outside public order books or against single market maker venues. In this sense, XR constitutes a natural experiment for assessing whether on-exchange segmentation can improve retail execution quality without undermining overall market integrity.

The introduction of XR offers a unique setting for causal inference. Because the functionality was implemented as a discrete market design change within an otherwise stable trading environment, it constitutes a natural experiment in on-exchange retail segmentation. The extension of XR to ETFs on March 3, 2025, provides a clear event date that isolates the treatment effect on a well-defined asset class. All other aspects of Xetra’s trading structure, such as matching algorithm, trading hours, and regulatory framework, remained unchanged, ensuring comparability before and after the event. Moreover, the concurrent trading of identical ETFs on Euronext Milan allows for a matched DiD approach that distinguishes the effect of XR from general market trends. This combination of institutional clarity and data granularity makes XR an ideal laboratory for studying how on-exchange retail segmentation affects execution quality and market performance.

Importantly, this paper focuses on the extension of XR to ETFs on March 3, 2025, rather than its initial launch for equities in May 2024. The early phase of the program was characterized by limited participation with only a few RLPs and RMOs being active, and trading volumes were relatively low.³ When ETFs were included,

³This statement is based on own analysis of XR trades in equities, which are available from the authors upon request.

the XR framework had reached a stable operational phase with several RLPs and RMOs being active, making the ETF extension a discrete and observable change in market design rather than a gradual buildup.

4. Execution Quality Analysis

This section first provides descriptive analyses on the occurrence of price improvement and subsequently investigates the factors driving both its probability and magnitude for XR executions in ETFs.

4.1. Execution quality data

The XR execution data provide detailed information on the instrument, execution price, trade size, and timestamp at nanosecond granularity. However, the data does not include the side of the retail order. Therefore, we make the assumption that RLPs do not quote on the opposite side of the midpoint.⁴ Notably, we only observe the portion of the RMO order flow that is executed against the RLP quotes while parts of retail orders executed in the CLOB remain unobserved, as no explicit link between these executions and the RLP trades can be established. To place each retail execution in the context of prevailing market conditions, we collect information from Xetra’s CLOB and all trades executed on Xetra within the 15 minutes preceding the retail execution, at the exact time of the execution, and for one minute thereafter. Additionally, we compute the total daily ETF volumes from market-wide Xetra executions during continuous trading to assess the volume share of XR in these volumes (we do not include auction volumes since XR is limited to continuous trading). The data is sourced from BMLL, a provider of historic trade and order book data.⁵

For the execution quality analysis, we obtain an initial dataset comprising 197,206 XR executions collected on 137 trading days over the period from March 3 to September 12, 2025. XR executions are observed in 249 of the 256 ETFs initially selected by Deutsche Börse for the inaugural launch of XR for ETFs. To ensure a sufficient level of XR activity, we exclude all ETFs with fewer than two executions per day on average, corresponding to fewer than 274 executions over the sample period. The resulting dataset comprises 114 ETFs and 181,143 executions. Thus, while 54.22% of ETFs are excluded in this step, only 8.15% of observations are removed. A comprehensive list of included ETFs is presented in [Appendix A](#). We also exclude 639 samples which are marked as executed outside BBO.⁶ We additionally exclude 1,128

⁴This assumption is plausible given that RLPs function as market makers and, therefore, do not submit quotes that cross the midpoint, which serves as a proxy for fair value. Moreover, discussions with representatives of Deutsche Börse confirmed that RLP quoting behavior adheres to this constraint. Accordingly, all executions occurring above the prevailing midpoint are classified as retail buy orders, while those below the midpoint are classified as retail sell orders. While this assumption is plausible, it necessitates the exclusion of those observations executed exactly at the prevailing midpoint from those parts of the analysis that require information on the order side.

⁵See <https://www.bmlitech.com/products/bml1-data-lab>.

⁶In these rare cases, a large XR trade may consume several price levels, producing multiple executions and removing the prevailing BBO. If each execution price is compared to a snapshot

midpoint executions which, despite receiving price improvement, do not allow us to infer the retail side needed to construct key variables. These two steps are applied after producing the XR outcome descriptive statistics in [Table 2](#) and before reporting the price-improvement statistics in [Table 3](#). After computing the price-improvement descriptive statistics ([Table 3](#)) and before the regressions, we drop 3,254 observations with a one-tick prevailing spread, as these offer no scope for RLP price improvement. This yields a regression sample of 176,112 XR executions spanning 114 ETFs over 137 trading days used for the probit model. The filtering steps are summarized in [Table 1](#). For the OLS model, we further restrict the sample to the 122,679 observations exhibiting price improvement to examine, conditional on an improvement occurring, the determinants of its magnitude.

Most importantly, we use the price, size, and inferred side of each XR execution in comparison with 10 levels of the respective side of the prevailing CLOB to compute a hypothetical execution of the same order in the CLOB. The difference between the actual and hypothetical execution prices is defined as the price improvement, measured in both ticks and bps, which serve as the dependent variables in the following OLS regressions. For the probit regressions, we define a price improvement dummy variable, which takes the value 1 for positive price improvements and 0 otherwise.

We use snapshots of the prevailing limit order book to compute the prevailing bid-ask spread (expressed in ticks and bps), the prevailing limit order book imbalance, and the prevailing level-1 depth. Additionally, we define a retail-buy dummy variable (1 for retail buy orders, 0 otherwise) and a same-side imbalance dummy, which equals 1 when the retail order is on the same side as the prevailing market pressure indicated by the order book imbalance. For a more detailed picture, we include an interaction term between the prevailing order book imbalance and the same-side imbalance dummy. For each execution, we compute the time-weighted average bid-ask spread, cumulative EUR trading volume, and realized volatility (standard deviation of returns), all over the 15-minute pre-execution window. Finally, the price impact of each execution is calculated as the change in the prevailing midpoint from the execution time to 15 seconds later, expressed in bps.

For the regressions, we take the logarithm of the variables order size, prevailing spread in ticks and bps, prior turnover and prevailing level-1 depth. To handle outliers, the regression data is winsorized at the 1% and 99% level. Comprehensive summary statistics for the data are provided in [Table A.15](#) for the probit regression and [Table A.16](#) for the OLS regression in the appendix.

4.2. Descriptives

[Figure 1](#) depicts the daily number of XR executions in our dataset ranging from the launch of XR for ETFs on March 3, 2025 to September 12, 2025. Execution counts are modest in the initial three weeks, indicating a transition period as RLPs established quoting activity and adjusted systems for the new segment. In April, we observe a

captured just before the trade starts (without updating quotes between fills), later executions can appear to occur away from the BBO, because the snapshot is stale.

Table 1: Sample Construction and Filtering Procedure Execution Quality Analysis

This table documents the sequential filtering steps used to construct the sample of ETFs used in the execution quality analysis. The initial dataset includes all ETFs applicable for XR on Xetra over the sample period. We first remove ETFs with insufficient XR trading activity (i.e., less than two XR trades per day on average). For later analyses, we exclude the few observations where XR trades were executed outside the best bid and offer, those executed at the midpoint so that we are not able to identify whether these trades are buyer- or seller-initiated and those where the prevailing spread in the regular Xetra order book was just one tick so that price improvement was not possible.

Step	Description	Remaining Obs.	Removed Obs.	Rem. ISINs	Rem. Days
1	Initial dataset	197,206	0	249	137
2	Remove < 2 trades per day on avg.	181,143	16,063	114	137
3	Remove outside BBO	180,504	639	114	137
4	Remove unknown side	179,366	1,138	114	137
5	Remove one tick prevailing spread	176,112	3,254	114	137

period with a high number of XR trades which coincides with the overall increased trading volume in the market around the U.S. “liberation day” when President Trump announced high tariff increases. Overall, we observe a steady increase in the number of XR executions per day over our observation period.

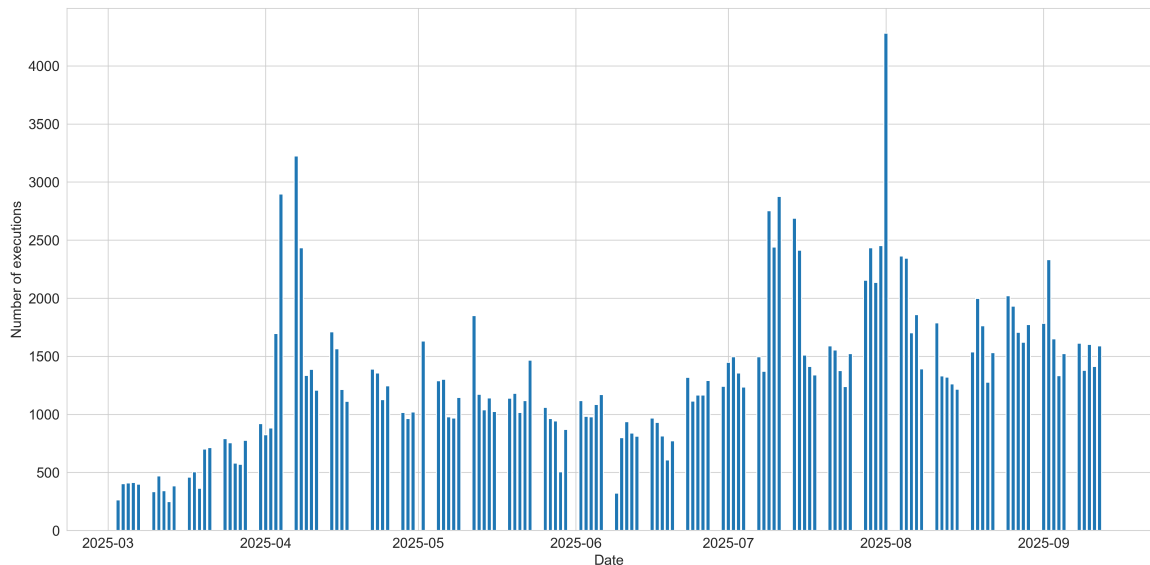


Figure 1: This figure plots the total number of XR executions per day (Y-axis) for 114 ETFs included in our analysis, over the period from March 3, 2025, to September 12, 2025 (X-axis).

The histogram in [Figure 2](#) plots the distribution of XR trade sizes, measured in EUR thousand. The horizontal axis denotes the trade size, ranging from small values near zero up to a cap of EUR 60 thousand. The maximum XR trade size is about EUR 1.5 million (EUR 1.17 million after winsorization), likely reflecting the execution of aggregated savings-plan orders routed by a retail broker. The distribution is strongly

right-skewed, with a pronounced concentration of trades at smaller sizes. The modal bin is located at the lowest trade size range, indicating that small trades dominate the execution landscape for retail flow. As trade size increases, the frequency of executions decays rapidly, with fewer trades observed above EUR 10 thousand. The histogram displays a long and sparse right tail, suggesting the presence of occasional large trades. This pattern is consistent with the notion that retail investors primarily transact in smaller quantities. This is also supported by the mean execution size (EUR 10.69 thousand) being considerably higher than the median (EUR 2.66 thousand).

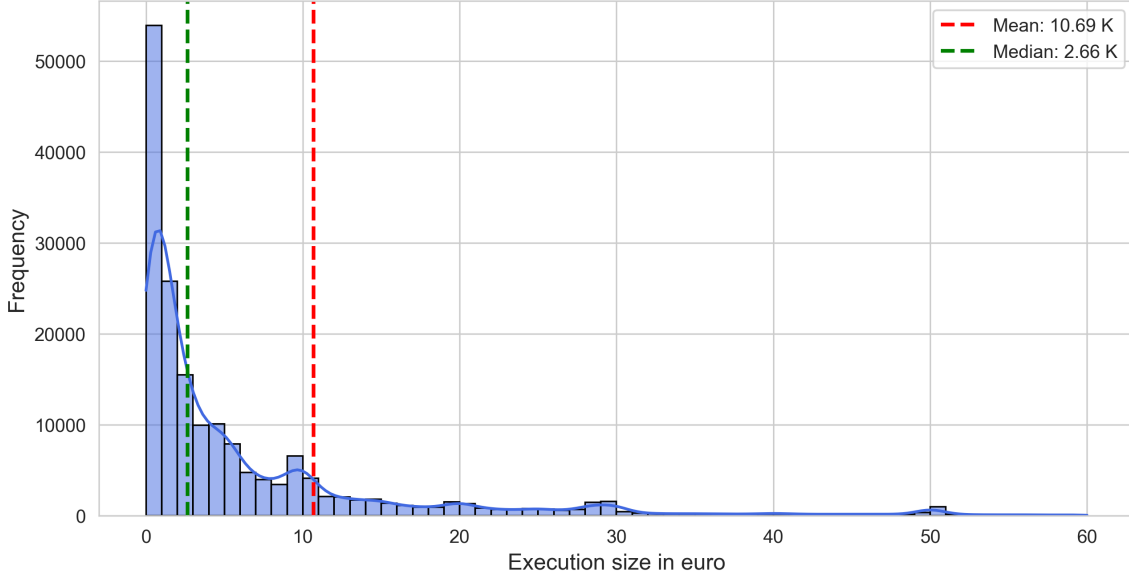


Figure 2: This figure presents a histogram of XR execution sizes in EUR thousand (X-axis) based on a sample of 181,143 executions in 114 ETFs with an average of more than two trades per day. For visualization purposes, the histogram is capped at EUR 60 thousand, while the reported mean and median execution sizes are calculated from the complete dataset.

As a first indication of the effects of XR on retail order executions, we examine the outcome of the execution price relative to the prevailing best bid and offer (BBO) on the CLOB, as summarized in Table 2. A majority of retail ETF executions (62.71%) occur between the best bid and best ask quotes, suggesting that most orders receive price improvement relative to the quoted spread. Approximately 12% of executions occur at the best bid, and 25% at the best ask, i.e., a substantial proportion of trades execute at prices identical to those in the regular CLOB. The higher proportion of executions occurring at the best ask level provides an initial indication that RLPs may exhibit a lower propensity to offer price improvement for retail buy orders. Only a very small fraction of executions (0.35%) is measured to occur behind the BBO (resulting from e.g. a very large order that consumes multiple order book levels in the CLOB including the RLP quote).⁷ The analysis of subgroups reveals some heterogeneity

⁷These these samples are later removed from the dataset.

Table 2: XR outcome summary by ETF category

This table reports the percentage distribution of execution outcomes relative to the prevailing CLOB for all ETFs and for the subcategories Stock ETFs, Bond ETFs, and Other ETFs. The column “All ETFs” presents results for the full sample, while the subcategories provide corresponding splits. The sample size for each category is indicated in the last row.

XR Outcome	All ETFs	Stock ETFs	Bond ETFs	Other ETFs
Between BBO	62.71	62.60	66.70	40.04
At Best Bid	11.89	12.01	9.21	23.57
At Best Ask	25.05	25.03	23.81	35.38
Behind BBO	0.35	0.35	0.28	1.00
Observations	181143.00	161399.00	17449.00	2295.00

across ETF categories. Bond ETFs exhibit the highest rate of price improvement (66.7%), whereas other ETFs (i.e., ETFs on commodities or those representing a mix of equities and bonds) display the lowest (40.04%), and correspondingly higher proportions at or behind the BBO. A more granular perspective on the XR outcome for different types of bond ETFs is provided in [Table A.13](#). While corporate bonds and government bonds show almost identical fractions of price improvements (both 66.7%), European government bonds denoted in EUR receive slightly less (61.5%) price improvement compared to other government bonds (74.8%), which primarily consist of US and global government bond baskets denoted in USD.

[Table 3](#) provides a summary of computed price improvement for retail ETF executions, broken down by category. For all ETFs, the average retail trade receives a price improvement of 1.30 ticks (0.93 bps) while the median price improvement is 1.00 tick (0.47 bps). Conditioned on receiving a price improvements, the average retail trades receives a price improvement of 1.89 ticks (1.35 bps). Bond ETFs and other ETFs exhibit the highest average price improvement (1.90 and 2.00 ticks, respectively), compared to equity ETFs (1.22 ticks). In basis points, however, equity ETFs achieve higher average improvement (0.98 bps) than bond ETFs (0.56 bps) and other ETFs (0.16 bps). This underscores the importance of differences in tick size across categories and highlights the need to examine price improvement from both tick and basis point perspectives in the subsequent analysis. The average trade size is largest for other ETFs (EUR 68 thousand), while bond ETFs and equity ETFs see smaller average trade sizes (EUR 12 thousand and EUR 9.6 thousand, respectively). A more granular view on different types of bond ETFs is provided in [Table A.14](#) in the appendix.

4.3. Methodology

We evaluate execution quality using two complementary regression approaches: first, a probit regression with the price improvement dummy as the dependent variable, and second, an OLS regression with the actual price improvement (measured in ticks and bps) as the dependent variable.

Table 3: XR price improvement summary by ETF category

This table presents summary statistics on price improvement for retail ETF orders executed via XR, as well as associated market conditions. Results are reported for the entire dataset ("All ETFs") and the subcategories "Stock ETFs", "Bond ETFs", and "Other ETFs". Statistics include average and median price improvement in both ticks and basis points, average and median trade size in EUR, and average and median quoted bid–ask spread in both basis points and ticks at the time of order arrival. The "Conditional" numbers report statistics for the subset of samples with positive price improvement. The sample size for each category is provided in the last row.

category	All ETFs	Stock ETFs	Bond ETFs	Other ETFs
Avg Price Improvement (ticks)	1.30	1.22	1.90	2.00
Median Price Improvement (ticks)	1.00	1.00	1.00	1.00
Mean Conditional PI (ticks)	1.89	1.80	2.52	2.67
Median Conditional PI (ticks)	1.00	1.00	1.00	1.00
Avg Price Improvement (bps)	0.93	0.98	0.56	0.16
Median Price Improvement (bps)	0.47	0.49	0.35	0.07
Mean Conditional PI (bps)	1.35	1.45	0.75	0.21
Median Conditional PI (bps)	1.11	1.21	0.41	0.09
Avg Trade Size (EUR)	10612.12	9631.32	12158.77	68196.57
Median Trade Size (EUR)	2642.67	2344.75	4705.20	19026.86
Avg Bid–Ask Spread (bps)	5.87	5.82	6.97	1.21
Median Bid–Ask Spread (bps)	4.15	4.09	5.44	1.02
Avg Bid–Ask Spread (ticks)	9.53	7.82	24.44	15.78
Median Bid–Ask Spread (ticks)	5.00	4.00	20.00	14.00
Observations (N)	180504.00	160832.00	17400.00	2272.00

Both approaches employ the same set of independent variables. These comprise the order-related variables *log_order_size_eur*, *retail_buy_dummy*, *price_impact_15s_bps*; the market context variables *log_prevaling_spread*, *prevailing_oib*, *log_prior_turnover*, *log_prevaling_L1_depth*, *prior_realized_volatility*, *tick_size*; as well as variables capturing the interaction between order characteristics and market conditions, namely *imbalance_same_side* and the interaction term *prevailing_oib* $\times$ *imbalance_same_side*. Moreover, both approaches are conducted in two variations, once with the spread measured in ticks and once in bps. In the OLS model, the dependent variable *price_improvement* is expressed in the corresponding unit.

4.3.1. Probit regression

The probit model uses *price_improvement_dummy* as the dependent variable. The estimated marginal effects quantify how variations in the covariates influence the probability of observing a price improvement, thereby identifying the main determinants of its occurrence.

The probit regression model is presented in the following [Equation 1](#):

$$\begin{aligned}
\Pr(y_i = 1 \mid X_i) = & \Phi(\alpha + \beta_1 \cdot \log_order_size_eur_i \\
& + \beta_2 \cdot retail_buy_dummy_i \\
& + \beta_3 \cdot \log_prevailing_spread_i^u \\
& + \beta_4 \cdot prevailing_oib_i \\
& + \beta_5 \cdot imbalance_same_side_i \\
& + \beta_6 \cdot \log_prior_turnover_i \\
& + \beta_7 \cdot \log_prevailing_L1_depth_eur_i \\
& + \beta_8 \cdot prior_realized_volatility_bps_i \\
& + \beta_9 \cdot price_impact_15s_bps_i \\
& + \beta_{10} \cdot (prevailing_oib_i \times imbalance_same_side_i) + \mu_i)
\end{aligned} \tag{1}$$

where i is the index for each observation, y is the binary target, Φ is the cumulative normal distribution, X_i is the list of regressor variables, and $u \in ticks, bps$ denotes the units of measurement and μ_i denotes ETF fixed effects.

4.3.2. OLS regression

The OLS model examines how the explanatory variables affect the magnitude of realized price improvement, conditional on a price improvement having occurred.

The OLS regression is shown by the following [Equation 2](#):

$$\begin{aligned}
price_improvement_i^u = & \alpha + \beta_1 \cdot \log_order_size_eur_i \\
& + \beta_2 \cdot retail_buy_dummy_i \\
& + \beta_3 \cdot \log_prevailing_spread_ticks_i^u \\
& + \beta_4 \cdot prevailing_oib_i \\
& + \beta_5 \cdot imbalance_same_side_i \\
& + \beta_6 \cdot \log_prior_turnover_i \\
& + \beta_7 \cdot \log_prevailing_L1_depth_eur_i \\
& + \beta_8 \cdot prior_realized_volatility_bps_i \\
& + \beta_9 \cdot price_impact_15s_bps_i \\
& + \beta_{10} \cdot (prevailing_oib_i \times imbalance_same_side_i) + \mu_i + \lambda_i + \varepsilon_i
\end{aligned} \tag{2}$$

where i is the index for each observation, $price_improvement_i^u$ is the target variable, $u \in ticks, bps$ denotes the units of measurement, μ_i and λ_i denote security and time (day) fixed effects, respectively, and $\varepsilon_{i,t}$ is the idiosyncratic error term.

4.4. Results

The marginal effects of the probit regression with entity fixed effects, for both the tick and basis-point (bps) specifications, are presented in [Table 4](#). The marginal

effects (dy/dx) represent the marginal change in the probability of price improvement associated with a one-unit increase in an explanatory variable, holding all other factors constant. For continuous variables entered in levels, this corresponds to the change in probability for a one-unit increase in that variable. For variables expressed in logarithms, the coefficient reflects the change in probability associated with an approximate 1% increase in the underlying variable. For dummy variables, the reported marginal effect indicates the discrete change in the probability of price improvement when the indicator variable shifts from 0 to 1.

A 1% increase in order size is associated with a 0.0134 (ticks specification) or 0.0135 (bps specification) percentage point increase in the probability of price improvement, indicating that larger orders are modestly more likely to obtain price improvement. Retail buy orders are 8.3 (bps specification) to 8.4 (ticks specification) percentage points less likely to receive price improvement compared to sell orders. This pattern likely reflects higher inventory costs for liquidity providers, given that retail investors tend to submit a greater proportion of buy orders. In our data set, 65% of XR executions in our data set originate from retail buy orders as shown in [Table A.15](#). The bid-ask spread exhibits the most pronounced effect among all variables considered. A 1% increase in the prevailing spread is associated with a 0.19 percentage point increase in the likelihood of price improvement in the ticks specification and a 0.21 percentage point increase in the bps specification. This reflects that wider spreads provide greater opportunities for RLPs to offer price improvement relative to the best quotes in the CLOB. The prevailing order book imbalance does not exhibit a significant effect on the probability of price improvement. This finding suggests that net order flow pressure alone is not a primary determinant, or that its influence may be subsumed by the interaction term. Being on the same side as the market pressure reduces the likelihood of price improvement by about 4.6 percentage points in both specifications. This may reflect cautious behavior on the part of the RLP, as market pressure typically signals a potential price movement in the opposite direction (e.g., [Chordia et al., 2002](#)). An increase of 1% in recent turnover is associated with a modest 0.004 (0.0038 for bps) percentage point decrease in the probability of price improvement. Greater depth at the BBO is weakly associated with an increased likelihood of price improvement in the tick specification, although this relationship is not statistically significant in the bps specification. A one bps increase in prior realized volatility is associated with a decrease in the probability of price improvement by approximately 0.38 percentage points in the ticks specification and by about 0.41 percentage points in the bps specification, suggesting that higher market risk discourages RLPs from offering price improvements. A one bps increase in price impact is associated with a reduction in the probability of price improvement by approximately 0.52 percentage points in the ticks specification and 0.53 percentage points in the bps specification. While this suggests that RLPs are to some extent able to avoid informed order flow correlated with higher price impact, the economic magnitude of the effect is not substantial. The marginal effects for the interaction between prevailing order imbalance and same-side imbalance indicate that a one-unit increase in the interaction term is associated with an increase in the probability of price improvement by approximately 8.9 percentage points. This result

is notable and somewhat puzzling, as it suggests that RLPs are more likely to grant price improvement precisely in situations where the market pressure is against them.

Table 4: Marginal effects of probit regression on price improvement dummy

This table reports the marginal effects (dy/dx) of a probit regression where the dependent variable is a binary indicator for price improvement. Results are shown for two models: one with log *prevailingspread* measured in ticks and one in bps. The regression is estimated on a sample of 176,112 observations across 114 ETFs, with standard errors clustered at the entity level. Key independent variables include log order size (in EUR), a retail buy order indicator, measures of prevailing spread (in ticks or bps), prevailing order imbalance, a dummy for “imbalance same side” (equal to one if the retail order is on the same side as the current market pressure), prior turnover, order book depth, realized volatility, price impact, and an interaction term capturing the joint effect of prevailing order imbalance and imbalance same side. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) levels. Pseudo R^2 values are 0.1186 and 0.1159 for the models in ticks and bps, respectively. All models include entity fixed effects.

Dep. Variable:	price improvement dummy	
Model:	[ticks]	[bps]
Variable	dy/dx	dy/dx
log order size	0.0134***	0.0135***
retail buy dummy	-0.0842***	-0.0831***
log prevailing spread ticks	0.1971***	
log prevailing spread bps		0.2119***
prevailing oib	-0.0082	-0.0030
imbalance same side	-0.0462***	-0.0467***
log prior turnover	-0.0041***	-0.0038***
log prevailing L1 depth	0.0086*	0.0023
prior realized volatility	-0.0038***	-0.0041***
price impact 15s	-0.0052***	-0.0053***
prevailing oib $\times$ imbalance same side	0.0887***	0.0882***
Entity FE	yes	yes
No. Observations:	176,112	176,112
Pseudo R^2 :	0.1186	0.1159

Table 5 presents the results of the OLS regression with entity fixed effects for both the tick and bps specifications.

Regarding the order characteristics, larger orders are associated with highly significant increases in price improvement which however is economically modest with a 1% increase in order size associated with a 0.000646 tick (or 0.000343 bps) increase in price improvement. Retail buy orders receive 0.31 fewer ticks (or 0.17 fewer bps) of price improvement. As for the market condition variables, a 1% increase in prevailing spread is associated with approximately 0.00944 additional ticks and 0.00537 additional bps of price improvement. A 1% increase in top-of-book depth reduces price improvement by approximately 0.000897 ticks or 0.000415 bps. As in the probit model, the order book imbalance does not show a significant standalone effect in either specification. The prior turnover has a modest positive effect on price improvement while the prevailing depth on the BBO has a modest negative effect. The volatility is only significant for the bps specification which shows a positive association with

Table 5: OLS regression results

This table reports coefficients from ordinary least squares (OLS) regressions where the dependent variable is price improvement, measured either in ticks or basis points (bps). Independent variables include log order size (in EUR), a retail buy order indicator, measures of the prevailing spread (in ticks or bps), prevailing order imbalance, a dummy for “imbalance same side” (equal to one if the retail order is on the same side as the current market pressure), prior turnover, order book depth, prior realized volatility, price impact, and an interaction term between prevailing order imbalance and the imbalance same side dummy. T-statistics are reported in parentheses. Standard errors, shown in parentheses, are double-clustered by entity and date. Both models use 122,679 observations and include entity and date fixed effects. Asterisks indicate statistical significance at the 1% (***), 5% (**), and 10% (*) levels. R^2 values are 0.0861 (ticks) and 0.1027 (bps), with F-statistics reported at the table’s bottom.

Dep. Variable	price improvement ticks	price improvement bps
	coef	coef
log order size	0.0646*** (7.1008)	0.0343*** (7.4892)
retail buy dummy	-0.3096*** (-7.3014)	-0.1689*** (-8.8810)
log prevailing spread ticks	0.9440*** (7.7558)	
log prevailing spread bps		0.5371*** (14.3045)
prevailing oib	-0.0168 (-0.7075)	0.0007 (0.0502)
imbalance same side	-0.2083*** (-6.7654)	-0.1066*** (-6.3264)
log prior turnover	0.0200*** (4.7747)	0.0049*** (3.5778)
log prevailing L1 depth	-0.0897*** (-4.9169)	-0.0415*** (-4.5329)
prior realized volatility	0.0095 (1.0964)	0.0162*** (5.0629)
price impact 15s	0.0198*** (4.0742)	0.0139*** (7.4187)
prevailing oib X imbalance same side	0.7915*** (9.3999)	0.3961*** (9.4749)
Entity FE	yes	yes
Day FE	yes	yes
No. Observations	122,679	122,679
R^2	0.0861	0.1027

price improvement. The price impact of the order is positively related to price improvement but of economically limited magnitude. The interaction term shows that when the retail order is on the same side as the market pressure, a higher imbalance is associated with higher price improvement.

To further assess the magnitude of the effects of the predictors of the OLS regression, we evaluate the relative importance of the predictors based on their respective contributions to the overall model fit (Adjusted R^2), following the decomposition approach proposed by [Groemping \(2006\)](#). The results stress that the prevailing spread both in ticks and in bps has with over 70% by far the strongest effect on the magnitude of price improvement. Interestingly, the volatility has a large importance in the bps denominated model while it is less dominant in the ticks model. The variable importance for all regressors is summarized in [Table 6](#).

Table 6: OLS regression variable importance

This table reports the relative importance of each variable in the OLS regressions for price improvement, measured both in ticks and basis points (bps). Relative importance is calculated as each variable's contribution to the model's adjusted R^2 , following the decomposition method of [Groemping \(2006\)](#). Results are shown in absolute terms and as a percentage of total model fit.

Model	[ticks]	[ticks]	[bps]	[bps]
Variables	relative importance	rel. imp. (percent)	relative importance	rel. imp. (percent)
log order size	0.0076	3.3388	0.0002	0.0612
retail buy dummy	0.0051	2.2424	0.0132	4.0264
log prevailing spread ticks	0.1782	77.7765		
log prevailing spread bps			0.2377	72.5685
prevailing oib	0.0015	0.6639	0.0016	0.5022
imbalance same side	0.0020	0.8754	0.0014	0.4323
log prior turnover	0.0030	1.2907	0.0043	1.2994
log prevailing L1 depth	0.0134	5.8523	0.0033	1.0174
prior realized volatility	0.0098	4.2987	0.0588	17.9510
price impact 15s	0.0007	0.3036	0.0015	0.4431
prevailing oib X imbalance_same_side	0.0077	3.3577	0.0056	1.6985

Although both the probit and OLS models employ an identical set of regressors, they address distinct research questions and are estimated on partially different samples. Specifically, the probit model analyzes the likelihood of a price improvement occurring, irrespective of the magnitude of improvement, and is estimated on the full dataset. In contrast, the OLS model is restricted to observations where a price improvement has already occurred and examines the determinants of the magnitude of this price improvement. Consequently, while the models are structurally similar with respect to their explanatory variables, the interpretation and comparability of estimated effects between the two are inherently limited due to differences in the dependent variables and estimation samples.

Nevertheless, both analyses exhibit notable commonalities. Across both the probit and OLS models, the prevailing bid-ask spread is the dominant driver of price

improvement, increasing both its likelihood and its magnitude and accounting for most of the explained variation of the OLS models. Larger orders receive slightly higher and more frequent price improvement. Retail buy orders are disadvantaged relative to sells, consistent with inventory-cost asymmetries given buy-heavy retail flow. Order book conditions matter asymmetrically: same-side imbalance reduces improvement on average, yet its interaction with the prevailing imbalance is positive in both models, indicating more improvement in certain high-pressure states despite the counterintuitive nature of this result. Risk and activity proxies differ across margins: volatility, price impact, and turnover reduce the probability of any improvement, but conditional on improvement they are associated with somewhat larger concessions (with volatility most relevant in the bps specification). Depth at the BBO is weakly positive for the probability but clearly negative for the size of improvement. With respect to the tick and bps specifications of both the probit and OLS models, the results are robust, with only one minor difference in significance level.

5. Market quality analysis

This section examines whether the introduction of XR, which enables retail orders to be executed against RLPs before interacting with the regular limit order book, adversely affects market quality in the main Xetra order book.

5.1. Market quality data

For the market quality analysis, we construct a panel dataset comprising daily measures of trading activity, liquidity, and volatility for ETFs traded on the treatment exchange, Xetra, and the control exchange, Euronext Milan (XMIL). Xetra is the largest European market for ETFs, with Euronext Milan constituting the second-largest venue. Accordingly, all observations from Xetra are classified as “Treat”. The event date, marking the launch of XR for the considered ETFs, is March 3, 2025. Observations on or after this date are classified as “Post”.

We analyze two distinct time horizons to capture both short-term and longer-term effects. The short-term window spans from February 1 to April 30, 2025, the longer-term window from January 1 to May 31, 2025. In our main analyses, two specific periods are excluded. The first exclusion covers March 3 to March 19, 2025, corresponding to the initial phase of XR trading for ETFs with limited XR shares in overall trading as depicted in [Figure 3](#). The second exclusion spans April 2 to April 11, 2025, a period characterized by exceptionally high market volatility and reduced liquidity following the “Liberation Day” which is also shown in [Figure B.6](#) and [Figure B.7](#) in [Appendix Appendix B](#). We exclude this period to prevent our results being biased from this phase of market turmoil.⁸ After these adjustments, the short-term window contains 40 trading days (20 pre-event and 20 post-event), and the longer-term window 83 trading days (42 pre-event and 41 post-event). We do not

⁸Nevertheless, we repeat all analysis including these two periods and find that our results are qualitatively similar, providing further evidence for the suitability of the control group and validity of the identified effects (see [Table 11](#)).

extend the observation period further because Euronext expanded its Best of Book offering to a set of the most liquid ETFs on XMIL on November 18, 2024 (Euronext, 2024). Including periods affected by this change could introduce ramp-up effects in the control market and bias the comparison, thereby compromising the validity of our identification strategy.

The sample construction begins with the 256 ETFs for which XR was initially introduced. From this universe, we retain 182 ETFs that are traded on both Xetra and Euronext Milan. This one-to-one matching of ETFs makes Euronext Milan an ideal control group for the event study, as it eliminates the need for synthetic treatment–control matching based on correlation or industry groupings, as employed in other studies. Consistent with Section 4, we exclude 91 ETFs with an average of fewer than two trades per day. Moreover, we remove 23 ETFs falling into the lowest quartile of XR share in continuous trading, using a cutoff value of 3.97% to ensure that we only analyze changes in market quality for ETFs where a relevant total trading volume in continuous trading was executed against RLPs via the XR mechanism. Applying these selection criteria yields a final sample of 68 ETFs for the main analyses. The final regression data set contains 5,210 observations (i.e., ETF-exchange-day combinations) for the short-term and 11,236 observations for the longer-term horizon. The data filtering steps are summarized in Table 7. In an additional robustness analysis, we also exclude those 18 ETFs for which Euronext Milan introduced the Best of Book mechanism in November 2024.⁹

Table 7: Sample Construction and Filtering Procedure Market Quality Analysis

This table documents the sequential filtering steps used to construct the sample of ETFs used in the market quality analysis. The initial dataset includes all ETFs applicable for XR on Xetra over the sample period. We first remove ETFs that are not traded on both Xetra and the control venue Euronext Milan, followed by those with insufficient XR trading activity (identical to the execution quality analysis). We then exclude ETFs in the lowest quartile of XR trading shares to ensure meaningful exposure to the XR mechanism. Finally, ETFs affected by the introduction of Euronext’s Best of Book (BoB) program on November 18, 2024 are excluded in robustness tests to maintain a clean control group. Columns report the number of ETFs (ISINs) and observations remaining after each step for the 40-day and 83-day event windows.

Step	Description	Remaing ISINs	Removed ISINs
1	Initial dataset	256	0
2	Remove not traded on both exchanges	182	74
3	Remove < 2 trades per day on avg.	91	91
4	Remove lower quartile XR share	68	23
5	Remove BoB event ETFs (robustness)	50	18

For the panel dataset, all variables are measured at the ETF–exchange–day level. Liquidity is captured using time-weighted order book measures, including the relative bid–ask spread, the EUR volume posted at the best bid and ask (Depth_L1), and cumulative quoted depth within 10, 30, and 50 basis points of the midpoint

⁹The results of the analysis excluding the 18 Best of Book-eligible ETFs are reported in Table 11.

(Depth(10), Depth(30), Depth(50)). Order book imbalance at the first level is computed as the absolute difference between bid and ask depth divided by their sum, yielding a bounded measure in $[0,1]$. Trading activity is measured by daily trading volume in EUR (denoted as turnover), the total number of shares traded (denoted as volume), and the number of trades. Volatility is proxied by the standard deviation of intraday midpoint returns sampled at one-minute intervals.¹⁰

These measures are chosen to analyze whether segmenting uninformed retail flow into XR affects market quality by increases the relative share of informed trading in the regular Xetra limit order book. If so, adverse-selection costs may rise, potentially reducing liquidity (higher spreads and lower depth), increasing imbalance and volatility, and depressing trading activity as a result of increased transaction costs. Importantly, XR trades are reported as regular Xetra trades with an XR flag. Therefore, changes in trading activity on Xetra reflect genuine shifts in total trading, rather than a mechanical reallocation between the lit book and XR.

To mitigate the influence of extreme values, all regression variables are winsorized at the 1% and 99% percentiles. Trading activity variables, including turnover, volume, and number of trades, are log-transformed.

5.2. Descriptives

Figure 3 illustrates the evolution of the daily share of ETF trading executed through XR in continuous trading. Following the XR launch, volumes increase steadily during the first three weeks, consistent with a ramp-up period in which RLPs gradually activate and scale their participation in ETFs.¹¹ From mid-March onward, XR executions stabilize at economically meaningful levels, regularly accounting for a relevant share of total ETF turnover on Xetra between 4% and 10%. Thereby, XR has become a relevant execution channel for retail flow shortly after its introduction. To avoid contamination from transitional dynamics and incomplete program participation, we exclude the initial ramp-up period from the DiD analysis and focus on the subsequent window in which XR activity has reached a steady state (see Table 7).

Standard summary statistics for all market-quality variables are reported in Table B.17 for Xetra and in Table B.18 for the same ETFs traded on XMIL in Appendix B. Since our identification strategy relies on a difference-in-differences design around the introduction of XR for ETFs on Xetra, Table 8 provides a pre-/post comparison of average market-quality measures for both trading venues around the event date of March 3, 2025 based on the longer-term event window of 83 trading days.

The table shows that most variables exhibit broadly similar trends across the two markets over the event window. Spreads widen on both Xetra and XMIL, consistent with higher market-wide volatility and tighter liquidity provision in the period follow-

¹⁰Specifically, volatility is calculated as the standard deviation of log returns of the order book midpoint on Xetra and XMIL during continuous trading, sampled at one-minute frequency and annualized assuming 8.5 trading hours per day and 252 trading days per year.

¹¹RMOs could register as early as January 2024, and participation grew while XR operated for equities. Accordingly, the March 2025 extension to ETFs primarily introduced fee rebates and retail execution functionality for ETFs, rather than triggering a new onboarding phase.

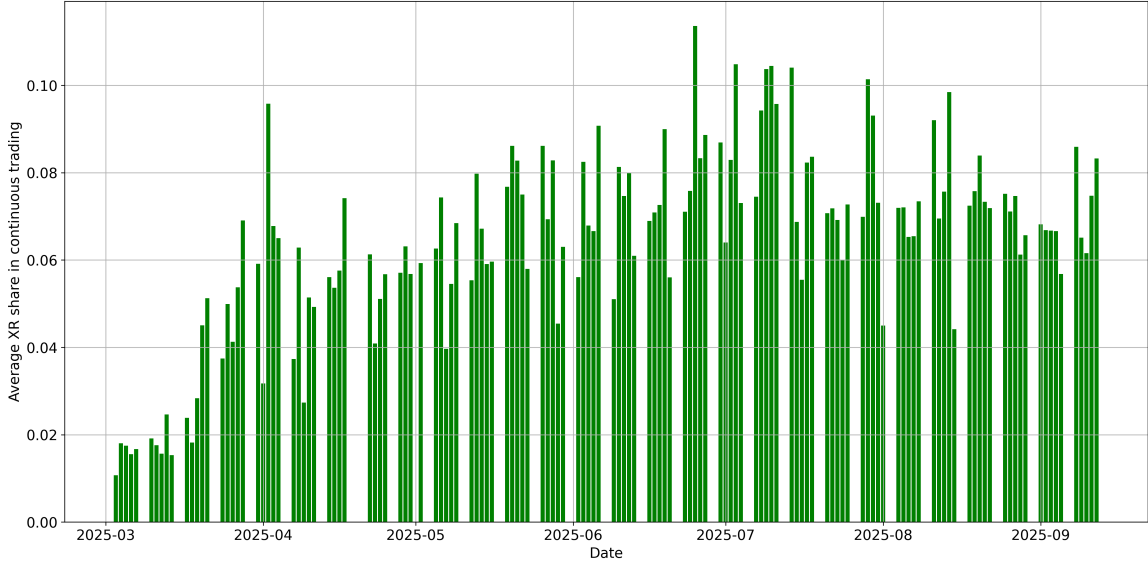


Figure 3: Daily share of XR executions in continuous trading for the analyzed ETF sample.

ing the XR launch. Trading activity declines moderately on both venues, reflected in lower trade counts, turnover, and volume, suggesting a common market environment rather than a venue-specific shock.

Depth measures decline more sharply on Xetra relative to XMIL, particularly within tight price bands around the midpoint (Depth₁₀ and Depth₃₀). This pattern is consistent with the hypothesis that routing uninformed retail flow to XR may reduce displayed liquidity incentives for competing liquidity providers at the top of book. Order-book imbalance evolves similarly across both venues, and the increase in volatility appears market-wide rather than Xetra-specific.

Overall, the raw pre-/post differences do not indicate a clear deterioration in Xetra market quality attributable to XR. These patterns motivate the formal DiD analysis to distinguish structural effects of XR from concurrent market-wide dynamics.

It is also noteworthy that trading volumes and depth levels are systematically higher on Xetra than on XMIL, consistent with Xetra's role as the largest venue for ETFs in Europe. These level differences are not problematic for the difference-in-differences design. More important for causal inference is the presence of parallel trends in the pre-event window. To assess this assumption, [Figure 4](#) plots the evolution of key market-quality measures, one representative variable from each dimension (liquidity, trading activity, depth, and volatility). The plots for the remaining set of variables are shown in [Figure 4](#) in the appendix.

The figure indicates a clear parallel pattern between Xetra and XMIL in the pre-event period, lending support to the suitability of XMIL as a control group. Following the introduction of XR, most series move similarly across both venues, consistent with common market-wide dynamics. The exception is quoted depth, where Xetra exhibits a more pronounced decline immediately after the event, followed by a partial recovery later in the sample. This descriptive pattern aligns with the hypothesis that XR may

Table 8: Pre-/Post Comparison of Market-Quality Measures Around XR Introduction (long-term window of 83 trading days)

This table reports average market-quality measures for the matched ETF sample on Xetra (XETR) and Euronext Milan (XMIL) during the 83-trading-day window surrounding the introduction of Xetra Retail (XR) for ETFs on March 3, 2025. “Pre” and “Post” denote averages before and after the event date, and “Rel. Change” represents the proportional difference between the two periods. Variables include quoted relative spread, trading activity (number of trades, turnover, trading volume), liquidity (depth at the best level and cumulative depth within 10, 30, and 50 basis points of the midpoint), order-book imbalance (OBI), and intraday volatility.

Variable	Venue	Pre	Post	Rel. Change
spread	XETR	6.596	7.955	0.206
	XMIL	8.709	10.131	0.163
trades	XETR	287.709	277.441	-0.036
	XMIL	99.133	91.152	-0.081
turnover	XETR	4.332	4.014	-0.073
	XMIL	1.449	1.312	-0.095
volume	XETR	79.524	72.652	-0.086
	XMIL	23.155	20.633	-0.109
Depth_L1	XETR	280.927	224.480	-0.201
	XMIL	256.970	234.406	-0.088
Depth_10	XETR	2,754.562	1,921.762	-0.302
	XMIL	1,705.794	1,439.182	-0.156
Depth_30	XETR	7,935.426	6,278.554	-0.209
	XMIL	4,850.524	4,178.072	-0.139
Depth_50	XETR	9,660.813	8,413.484	-0.129
	XMIL	5,498.891	5,099.725	-0.073
OBI	XETR	0.250	0.221	-0.116
	XMIL	0.239	0.211	-0.117
volatility	XETR	0.094	0.116	0.232
	XMIL	0.104	0.119	0.149

initially reduce displayed liquidity incentives, a question examined more formally in the DiD analysis that follows.

5.3. Methodology

To identify the causal impact of the introduction of XR on market quality, we estimate the following DiD model presented in [Equation 3](#):

$$\begin{aligned}
Y_{i,m,t} = & \alpha + \beta_1 \text{Treat}_{i,m} \times \text{Post}_t + \beta_2 \text{Treat}_{i,m} + \beta_3 \text{turnover}_{i,m,t} \\
& + \beta_4 \text{inv_price}_{i,m,t} + \beta_5 \text{volatility}_{i,m,t} + \beta_6 \text{spread}_{i,m,t} \\
& + \beta_7 \text{Depth_L1}_{i,m,t} + \mu_i + \lambda_t + \varepsilon_{it}
\end{aligned} \tag{3}$$

where Y_{imt} denotes the market quality metric for ETF i traded on market m (Xetra or Euronext Milan) on day t . The dependent variable alternately represents measures of *liquidity* (relative quoted spread and order book depth measures), *trading activity* (turnover, volume, number of trades), *volatility*, or *order-book imbalance*. $\text{Treat}_{i,m}$ is a binary indicator equal to one for ETFs traded on Xetra and zero for

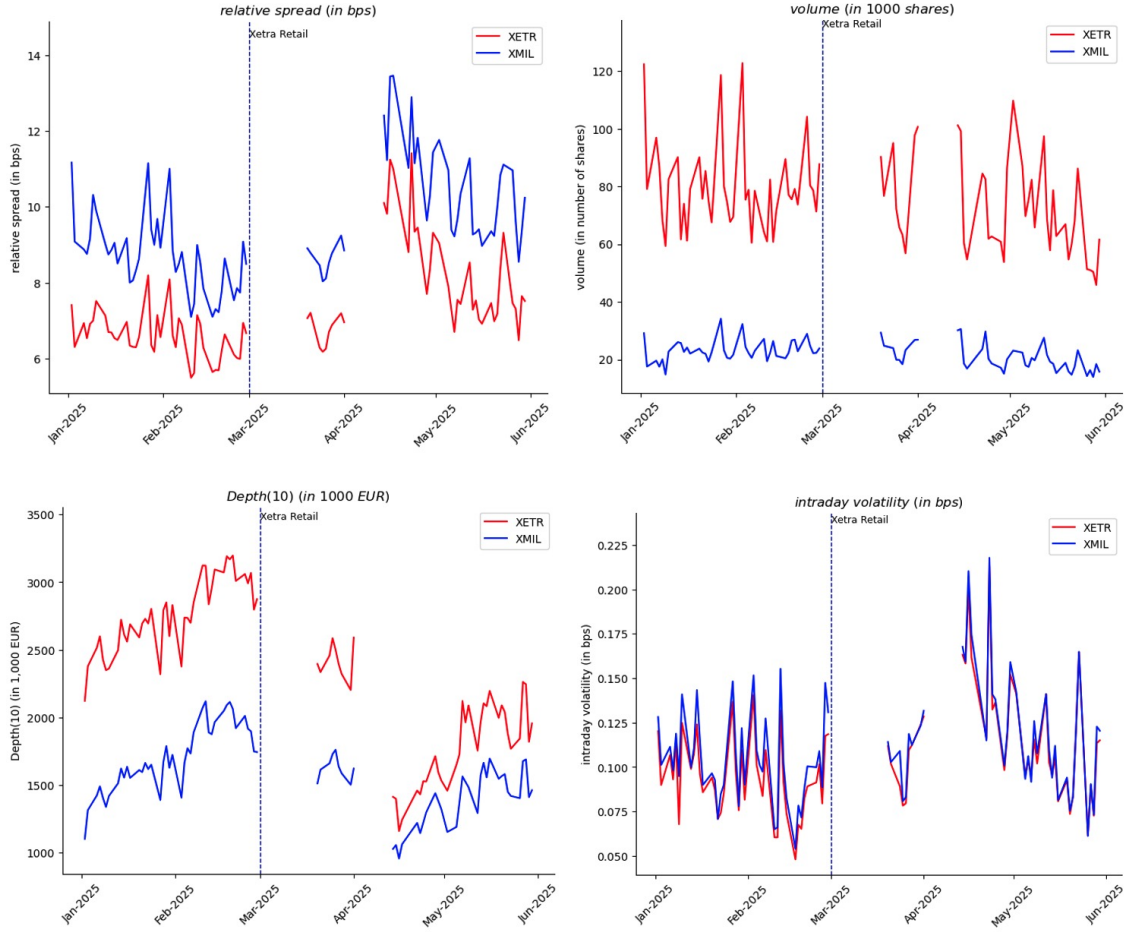


Figure 4: Average development of selected market quality variables on Xetra and XMIL around the introduction of XR. The white areas without plotted observations correspond to periods excluded from the analysis, namely the initial ramp-up phase after the introduction of XR for ETFs and the short episode of market turbulence around “Liberation Day”, where abnormal volatility and reduced liquidity conditions could confound the estimation.

the matched control group of identical ETFs listed on Euronext Milan’s *ETFplus* market. $Post_t$ equals one for the post-treatment period following the extension of XR to ETFs on March 3, 2025, and zero otherwise. The interaction term ($Treat_{i,m} \times Post_t$) identifies the average treatment effect of XR on the respective market quality measure, captured by β_1 .

Control variables include ETF-specific trading characteristics such as trading volume in EUR in ETF i on day t on market m , the inverse price level, volatility, the quoted spread, and depth at the first order book level. μ_i and λ_t denote ETF and time fixed effects, respectively, and ε_{it} is the error term. Standard errors are heteroskedasticity robust and double-clustered at the day and ETF level. Control variables are omitted when Y_{imt} is from the same market quality dimension (i.e., spread and Depth_L1 are omitted as control if a liquidity measure or order book imbalance is the dependent variable and turnover is omitted when one of the trading activity measures is the dependent variable).

5.4. Results

Table 9 reports the DiD estimates examining the effect of the introduction of XR on ETF market quality in terms of liquidity. The coefficient of interest is the interaction term ($Treat_{i,m} \times Post_t$), which captures the differential change in market quality on Xetra relative to Euronext Milan after XR went live. The coefficient on the treatment interaction term is statistically insignificant for quoted spreads, indicating that the introduction of XR did not widen spreads in the Xetra lit order book relative to the control market. This suggests that diverting retail flow to the XR mechanism did not increase adverse selection risk for liquidity providers nor impair pricing competition on the exchange.

By contrast, we find a consistent and statistically significant decline in displayed depth across all measures. Depth at the top of the book (Depth_L1) decreases by approximately EUR 34 thousand, about 12% relative to the pre-event level (see Table 8), while cumulative depth within 10, 30, and 50 basis points falls by EUR 570 thousand, EUR 991 thousand, and EUR 863 thousand, corresponding to relative reductions of 21%, 12%, and 9%, respectively. These effects represent meaningful but moderate reductions in displayed liquidity. The pattern is consistent with market makers partially adjusting their quoting strategies when some retail order flow becomes accessible through a dedicated mechanism. Importantly, these depth reductions occur in the absence of spread widening, suggesting that liquidity provision remains competitive, but some liquidity migrates from visible limit orders to XR quotes or to lower levels in the lit book.

Table 10 shows that all other dimensions of market quality remain unaffected. The treatment interaction is statistically insignificant for order-book imbalance, number of trades, traded volume, and turnover, indicating that the introduction of XR did not crowd out trading activity or cause systematic shifts in trading behavior on Xetra relative to XMIL. Volatility also remains statistically unchanged, consistent with the view that price discovery and risk dynamics in the main order book were not impaired.

Taken together, the results indicate that XR did not weaken overall market quality on Xetra. While there is some evidence of reduced top-of-book depth, the absence

Table 9: DiD Estimates – Liquidity Measures

This table reports coefficient estimates from a DiD panel regression evaluating the effect of the introduction of XR for ETFs on liquidity in the central limit order book on Xetra based on the longer-term observation period covering 83 trading days. The dependent variables are the quoted relative spread (in basis points) and displayed depth at the best level (Depth_L1) and within 10, 30, and 50 basis points of the midpoint (in EUR thousands). The $Treat \times Post$ interaction identifies the average treatment effect of the XR launch for ETFs listed on Xetra relative to the same ETFs on Euronext Milan. All regressions include ETF and day fixed effects and control for volatility, inverse price, turnover, and spread (except when the spread is the dependent variable). Standard errors are double-clustered by ETF and trading day. Statistical significance is denoted by $*p < 0.1$, $**p < 0.05$, and $***p < 0.01$.

	spread	Depth_L1	Depth_10	Depth_30	Depth_50
Treat x Post	0.0420 (0.2137)	-34.083*** (-2.8149)	-569.57*** (-5.3606)	-991.21*** (-3.3885)	-863.06*** (-2.6759)
Treat	-0.3314 (-1.1542)	0.7083 (0.0328)	937.81*** (3.4098)	2917.0*** (6.0838)	3989.7*** (7.6868)
turnover	-1.1494*** (-4.7178)	22.255** (2.2091)	118.81 (1.5961)	214.13* (1.6986)	259.11* (1.7880)
inv_price	68.531* (1.6576)	-1910.7 (-0.9593)	1.199e+04 (0.9853)	4.707e+04** (2.2604)	9732.7 (0.5436)
volatility	23.587*** (5.1709)	-206.04*** (-4.1610)	-1376.9*** (-2.6455)	-5167.3*** (-3.6566)	-5648.2*** (-4.2088)
spread		4.0470** (2.2572)	19.141 (1.6418)	57.072** (2.1314)	79.013*** (2.7745)
Entity FE	yes	yes	yes	yes	yes
Day FE	yes	yes	yes	yes	yes
No. Observations	11128	11128	11128	11128	11128
R-Squared (Within)	0.3377	0.0348	0.1459	0.2670	0.3709

of effects on spreads, volatility, and trading activity suggests that the introduction of XR did not increase adverse selection risk. Instead, these findings support the view that retail segmentation via integrated mechanisms such as XR can coexist with a healthy central limit order book.

Results based on the shorter 40-day event window are virtually identical, confirming that the findings are not sensitive to the sample horizon. The estimates of this analysis are reported in [Table B.19](#) and [Table B.20](#) in [Appendix B](#).

To assess the stability of the main DiD results, we conduct two sets of robustness checks: (i) excluding ETFs that became eligible for Euronext’s Best of Book program in November 2024, and (ii) re-estimating the baseline specification without excluding the initial XR ramp-up phase and the temporary market turmoil surrounding Liberation Day. [Table 11](#) reports the resulting treatment effects for all market quality measures across both the short- and long-term windows. Across specifications, estimated effects remain highly consistent with the baseline results. Spread effects remain statistically indistinguishable from zero, and no systematic changes emerge in trading activity, order-book imbalance, or volatility. Depth decreases persist across all robustness exercises—particularly at narrower depth bands—confirming a mild

Table 10: DiD Estimates – Trading Activity, Order Imbalance, and Volatility

This table reports coefficient estimates from a DiD panel regression evaluating the effect of the introduction of XR for ETFs on trading activity and price dynamics based on the longer-term observation period covering 83 trading days. The dependent variables are order-book imbalance at the first order book level (OBI), number of trades, turnover (EUR millions), traded volume (in thousands of shares), and intraday volatility (in basis points). The $Treat \times Post$ interaction identifies the average treatment effect of the XR launch for ETFs listed on Xetra relative to the same ETFs on Euronext Milan. All regressions include ETF and day fixed effects and control for volatility, inverse price, spread, Depth_L1 (except when OBI is the dependent variable), and turnover (except when the a trading activity measure is the dependent variable). Standard errors are double-clustered by ETF and trading day. Statistical significance is denoted by $*p < 0.1$, $**p < 0.05$, and $***p < 0.01$.

	OBI	trades	turnover	volume	volatility
Treat x Post	-0.0003 (-0.0233)	-0.0268 (-0.6708)	-0.0039 (-0.0797)	-0.0066 (-0.1337)	0.0052 (1.5169)
Treat	0.0065 (0.4551)	1.0828*** (10.115)	1.2420*** (11.107)	1.2467*** (11.119)	-0.0079*** (-2.7567)
turnover	-0.0021 (-0.5257)				0.0046*** (4.9857)
spread	-0.0025** (-1.9851)	-0.0727*** (-5.3811)	-0.1039*** (-8.8395)	-0.1037*** (-8.9118)	0.0040*** (4.5330)
inv_price	-0.0705 (-0.0239)	-9.4115 (-1.2981)	-9.9117 (-1.2596)	-0.6423 (-0.0870)	0.5732 (1.4092)
volatility	-0.0379 (-0.6336)	1.8808*** (4.3536)	2.4052*** (4.9237)	2.5317*** (5.1539)	
Depth_L1		0.0001 (0.4033)	0.0007*** (2.9424)	0.0007*** (2.8662)	-1.201e-05** (-2.3876)
Entity FE	yes	yes	yes	yes	yes
Day FE	yes	yes	yes	yes	yes
No. Observations	11128	11128	11128	11128	11128
R-Squared (Within)	0.0053	0.5415	0.4692	0.4698	0.1873

but robust deterioration in quoted depth on Xetra relative to the control venue. Importantly, these results hold even when including periods of elevated volatility and transient liquidity stress, underscoring that the control group appropriately captures broader market dynamics and isolated the treatment effect.

Although the DiD design and parallel-trend evidence support a credible identification strategy, some limitations remain. Unobserved shocks that differentially affect Xetra and Euronext Milan cannot be fully excluded, and dual-listed ETFs may be more liquid and internationally traded than the broader ETF universe, limiting generalizability. Moreover, structural microstructure differences across venues could still influence relative outcomes. These caveats suggest caution in extrapolating beyond the sample and underscore the value of future work examining longer horizons and alternative control settings.

Table 11: Robustness of DiD Estimates

This table reports robustness checks for the estimated treatment effect of the introduction of XR on market quality. Each cell presents the coefficient on the $Treat \times Post$ interaction from separate DiD regressions using alternative sample definitions. Columns (1) and (2) exclude ETFs that became eligible for Euronext’s BoB program in November 2024, and columns (3) and (4) re-estimate the baseline specifications without excluding the XR ramp-up phase and the market turmoil surrounding “Liberation Day”. Results are shown for both the short- and longer-term event windows. Dependent variables include spreads, quoted depth, order book imbalance, trading activity measures, and intraday volatility (units indicated in the first column). The control variables are identical to the main analysis. All regressions include ETF and day fixed effects, with standard errors double-clustered by ETF and trading day. Statistical significance is denoted by $*p < 0.1$, $**p < 0.05$, and $***p < 0.01$.

Dependent Variable	Dropped BoB ISINs (Short Term)	Dropped BoB ISINs (Long Term)	No excluded periods (Short Term)	No excluded periods (Long Term)
spread	-0.277	-0.130	-0.132	-0.022
Depth_L1	-27.762***	-14.422	-26.791***	-29.101**
Depth_10	-362.612***	-385.606***	-473.111***	-506.911***
Depth_30	-580.009**	-564.982**	-875.680***	-988.074***
Depth_50	-655.930***	-410.744	-1,034.309***	-944.750***
OBI	0.025	-0.002	0.016	0.003
trades	-0.039	-0.102**	0.003	-0.032
turnover	0.006	-0.057	0.056	0.003
volume	0.002	-0.058	0.051	0.001
volatility	0.007***	0.007***	0.005***	0.004***

6. Conclusion

This paper examines the introduction of Xetra Retail (XR) for ETFs, a novel on-exchange retail segmentation mechanism that integrates retail order flow into the central limit order book while allowing competition between dedicated Retail Liquidity Providers (RLPs) and regular order-book participants. Theoretical work highlights a fundamental trade-off in retail order flow segmentation: while retail investors may benefit through improved execution prices, segmentation can increase adverse selection costs for liquidity providers on the primary market, potentially degrading overall market quality. Our findings contribute directly to this debate.

We first document that XR delivers meaningful execution benefits to retail investors. Nearly 63% of all retail trades receive executions at prices better than the prevailing top-of-book quotes, with an average improvement of 0.93 basis points across all trades (1.35 basis points conditional on receiving an improvement). Price improvement is primarily driven by the width of the prevailing spread—consistent with liquidity providers having greater scope to offer incremental price enhancement when spreads are wider. Sell orders receive improvements more frequently than buy orders, in line with retail trading in ETFs being buy-dominated and RLPs managing inventory more efficiently by internalizing sell flow. Higher volatility reduces the likelihood of price improvement, reflecting increased adverse selection risk. Interestingly, larger orders are more likely to receive price improvement and at higher magnitudes,

although the economic effect is smaller than that of spreads or volatility. Together, these results suggest that XR channels uninformed retail flow to competing liquidity providers who pass on meaningful price improvements while efficiently managing risk.

Regarding overall market quality, our difference-in-differences analysis finds no evidence that XR adversely affected market quality on the primary Xetra order book relative to identical ETFs traded on Euronext Milan. Relative quoted spreads, trading activity, order-book imbalance, and intraday volatility remain statistically unchanged after XR's introduction, while quoted depth declines modestly. This pattern suggests a small reduction in displayed liquidity but no deterioration in other dimensions of market quality. Importantly, these conclusions are robust across alternative event windows and sample definitions, including specifications that retain the XR ramp-up period and the temporary market turbulence surrounding Liberation Day.

Taken together, our results provide evidence that XR improves retail execution quality without impairing overall market functioning. Against the theoretical trade-off highlighted in the segmentation literature, the introduction of XR appears to deliver private gains to retail investors without imposing measurable negative externalities on the broader market. These findings are particularly relevant in light of the forthcoming EU-wide prohibition of payment-for-order-flow arrangements: They show that exchange-integrated retail execution mechanisms can deliver price improvements while preserving market quality, suggesting a potentially viable model for post-PFOF European equity and ETF trading.

Our analysis opens several avenues for further work. First, extending the empirical setting to equities would allow testing whether results generalize beyond ETFs, which may exhibit distinct liquidity-provision dynamics due to their diversified nature. Second, a direct comparison of XR with other European retail execution mechanisms, most notably Euronext's Best of Book, would provide insight into how design differences shape retail outcomes and market quality. Third, future research could exploit proprietary data on RLP quoting behavior to study when and how RLPs supply liquidity, and whether price-improving quotes differ systematically from regular order-book quotes in size, timing, or persistence. Such micro-structure-level evidence would illuminate the competitive dynamics driving price improvement in exchange-integrated retail facilities.

As retail participation continues to rise and European market structure evolves in response to regulatory reform, understanding how to balance investor protection with market-wide efficiency remains central. This paper provides early evidence that appropriately designed on-exchange retail segmentation can support both objectives.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT 5 in the writing process in order to check grammar and improve the readability and language of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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Appendix A. Execution Quality Analysis

Table A.12: Execution quality analysis list of ISINs

isin	count	trades	sum turnover	mean pi ticks	mean pi bps
DE0002635273	312		2334037.610000	0.960000	1.820000
DE0002635281	345		3599244.480000	1.030000	1.360000
DE0002635307	1828		22815946.810000	0.530000	0.840000
DE0005933923	1681		26834316.990000	0.660000	1.350000
DE0005933931	2310		49282313.310000	0.760000	0.910000
DE0005933956	722		9893473.040000	0.570000	0.810000
DE0005933972	382		3530676.520000	1.180000	1.880000
DE0006289382	1257		12810579.970000	1.190000	1.460000
DE000A0F5UF5	2039		31079958.070000	0.900000	1.050000
DE000A0F5UH1	1901		16513195.920000	0.720000	1.200000
DE000A0Q4RZ9	447		21314792.890000	2.680000	0.180000
FR0010315770	845		8701294.580000	3.470000	1.080000
FR0010510800	577		33720136.900000	2.770000	0.250000
FR0010524777	542		2171063.040000	1.260000	2.440000
FR0010527275	506		3403912.420000	1.170000	1.790000
FR0010755611	745		7417783.240000	1.630000	2.480000
IE0001UQQ933	474		6984664.980000	1.560000	2.730000
IE0006WW1TQ4	1926		20810232.550000	1.060000	1.700000
IE000716YHJ7	870		4622377.790000	1.080000	1.660000
IE000I8KRLL9	860		3495938.270000	1.650000	2.370000
IE000OJ5TQP4	3464		25308878.090000	0.930000	1.290000
IE000RHYOR04	523		15694034.710000	0.990000	0.360000
IE000Y77LGG9	284		4001267.120000	1.030000	1.120000
IE000YYE6WK5	9042		58321740.110000	0.740000	0.890000
IE0031442068	1503		24473838.410000	2.270000	0.610000
IE0032077012	1365		10143201.500000	0.780000	0.850000
IE00B0M62Q58	1050		13938023.890000	3.120000	0.900000
IE00B0M62S72	280		1686530.510000	0.680000	1.360000
IE00B0M63177	469		3076009.610000	4.200000	1.100000
IE00B1TXK627	905		3941829.660000	1.120000	1.780000
IE00B1XNHC34	2660		5823229.910000	1.110000	1.650000
IE00B1YZSC51	467		5467793.910000	0.700000	1.070000
IE00B2NPKV68	281		2560005.120000	4.910000	1.270000
IE00B3B8Q275	3616		20101680.700000	1.730000	0.610000
IE00B3F81R35	3904		41689122.840000	1.040000	0.430000
IE00B3RBWM25	2262		31438678.880000	0.700000	1.150000
IE00B3VVMM84	468		3891599.150000	1.140000	2.000000
IE00B3WJKG14	4305		26028393.660000	0.560000	0.930000
IE00B3XXRP09	1767		24084272.330000	2.590000	0.710000
IE00B3YLTY66	1106		14311797.630000	0.730000	1.230000
IE00B3ZW0K18	489		13078417.720000	2.350000	0.970000
IE00B43HR379	669		4209517.270000	1.350000	1.550000
IE00B44Z5B48	611		9351630.640000	0.730000	1.190000
IE00B4K48X80	1167		25697495.520000	0.740000	0.900000
IE00B4L5Y983	13328		159679394.770000	1.800000	0.500000
IE00B4L5YC18	1144		8842458.260000	2.780000	0.750000

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isin	count	xr trades	sum turnover	mean pi ticks	mean pi bps
IE00B4L5YX21	398		2864896.960000	3.230000	0.980000
IE00B4L60045	485		7696666.880000	2.020000	0.930000
IE00B4WXJJ64	446		13683326.750000	1.360000	0.620000
IE00B4X9L533	1853		21346363.800000	2.650000	0.810000
IE00B52MJY50	276		1698518.640000	1.110000	1.290000
IE00B52VJ196	840		13136746.780000	0.840000	1.240000
IE00B53L3W79	747		9508420.080000	0.830000	1.190000
IE00B53L4350	351		3843427.800000	1.260000	1.410000
IE00B53SZB19	6047		71237478.700000	0.640000	0.910000
IE00B57X3V84	495		3353598.360000	1.170000	1.750000
IE00B5BMR087	10485		99808917.180000	1.210000	0.400000
IE00B60SX394	570		6603902.640000	2.560000	0.850000
IE00B652H904	589		2902638.490000	1.310000	1.890000
IE00B66F4759	3981		32426390.590000	2.150000	0.460000
IE00B6R52036	1229		6311055.390000	1.960000	3.300000
IE00B6R52259	2464		25977570.090000	0.720000	0.910000
IE00B6YX5C33	4769		39881953.890000	1.770000	0.520000
IE00B6YX5D40	1035		7011495.780000	0.940000	1.440000
IE00B8GKDB10	2059		24539539.260000	0.770000	1.230000
IE00B945VV12	556		4535214.790000	0.890000	1.090000
IE00B9CQXS71	972		4762597.300000	0.940000	1.550000
IE00B9MRHC27	336		2041550.810000	1.700000	1.920000
IE00BCRY6557	967		29923276.880000	0.730000	0.360000
IE00BDS67326	345		3562760.840000	6.220000	2.250000
IE00BDZZTM54	386		2386424.330000	1.160000	1.420000
IE00BF4RFH31	2623		14755896.840000	0.910000	1.340000
IE00BFMNPS42	379		4491209.120000	1.030000	1.690000
IE00BFMXXD54	6057		18002031.650000	1.200000	0.500000
IE00BFNM3J75	412		2678670.230000	0.810000	0.880000
IE00BFNM3P36	312		1247810.690000	1.170000	1.840000
IE00BFXR5W90	407		3730090.530000	1.130000	1.740000
IE00BFY0GT14	1437		16794231.120000	3.270000	0.940000
IE00BG0J4C88	1638		4764237.400000	1.160000	1.410000
IE00BG143G97	283		2240015.380000	0.820000	1.230000
IE00BGHQ0G80	885		7991939.480000	1.180000	1.590000
IE00BGV5VN51	2967		22693793.760000	0.640000	0.950000
IE00BHZRQZ17	687		4590681.240000	1.190000	1.550000
IE00BJ0KDQ92	3023		44761034.060000	1.900000	0.710000
IE00BJ0KDR00	334		4899377.950000	2.150000	0.710000
IE00BJ38QD84	3502		17113727.600000	0.830000	1.410000
IE00BJZ2DD79	1231		19763210.700000	0.730000	1.340000
IE00BK1PV551	1261		25625824.630000	3.130000	0.700000
IE00BK5BQT80	10132		48611158.240000	0.320000	0.480000
IE00BKM4GZ66	1291		13758390.690000	1.960000	0.610000
IE00BM67HK77	688		7674322.030000	1.140000	1.280000
IE00BM67HT60	728		7671351.590000	0.970000	1.180000
IE00BM8R0J59	341		1997081.670000	2.160000	3.120000
IE00BMC38736	523		2812137.870000	1.260000	1.620000
IE00BTJRMP35	999		15040865.570000	1.900000	0.640000
IE00BYX2JD69	537		6549355.510000	0.790000	1.420000

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isin	count xr trades	sum turnover	mean pi ticks	mean pi bps
IE00BYZK4552	557	3832728.150000	0.980000	1.570000
IE00BYZTVT56	2163	19483607.430000	2.670000	0.560000
IE00BZ02LR44	408	3404038.000000	0.870000	1.120000
IE00BZCQB185	1066	10894184.380000	1.040000	1.220000
LU0274208692	607	6721814.390000	2.180000	0.800000
LU0274209740	3584	38652828.780000	2.690000	0.710000
LU0274211217	2892	32123732.480000	0.580000	1.040000
LU0274211480	1244	27351679.480000	0.480000	0.900000
LU0290358497	1439	107818789.000000	1.520000	0.100000
LU0328475792	443	4388469.460000	0.790000	1.160000
LU0335044896	279	13871912.640000	2.290000	0.180000
LU0380865021	385	4970385.060000	0.680000	0.740000
LU0411075020	299	3815713.380000	0.790000	1.410000
LU0629459743	284	2863984.760000	0.920000	1.250000
LU0779800910	325	2828708.280000	2.080000	3.090000
LU0908500753	837	27864359.750000	0.390000	0.760000
LU1109943388	291	4939319.280000	2.820000	1.210000
NL0011683594	984	11556484.940000	1.070000	1.260000

Table A.13: XR Outcome Summary by Bond ETF Category

This table reports the percentage distribution of execution outcomes relative to the prevailing CLOB for all Bond ETFs and for the subcategories Corporate Bond ETFs, Government Bond ETFs, European Government Bond ETFs, and Other Government Bond ETFs. The column "Bond ETFs" presents results for all Bond ETFs, while the subcategories provide corresponding splits. The sample size for each category is indicated in the last row.

XR Outcome	Bond ETFs	Corp. Bonds	Gov. Bonds	EUR Gov. Bonds	Other Gov. Bonds
Between BBO	66.70	66.68	66.95	61.48	74.76
At Best Bid	9.21	8.58	15.80	19.37	10.70
At Best Ask	23.81	24.49	16.59	18.14	14.38
Behind BBO	0.28	0.24	0.66	1.01	0.16
Observations	17449.00	15930.00	1519.00	893.00	626.00

Table A.14: XR Price Improvement by Bond ETF Category

This table presents summary statistics on price improvement for XR bond ETF executions via XR, as well as associated market conditions. Results are reported for "All Bond ETFs" and the subcategories "Corporate Bond ETFs", "Government Bond ETFs", "European Government Bond ETFs", and "Other Government Bond ETFs". Statistics include average and median price improvement in both ticks and basis points, average and median trade size in EUR, and average and median quoted bid-ask spread in both basis points and ticks at the time of order arrival. The sample size for each category is provided in the last row.

category	Bond ETFs	Corp. Bonds	Gov. Bonds	EUR Gov. Bonds	Other Gov. Bonds
Avg Price Improvement (ticks)	1.90	1.75	3.55	2.08	5.64
Median Price Improvement (ticks)	1.00	1.00	1.00	1.00	1.00
Avg Price Improvement (bps)	0.56	0.52	0.99	0.40	1.81
Median Price Improvement (bps)	0.35	0.35	0.36	0.13	0.36
Avg Trade Size (EUR)	12158.77	10752.89	26963.85	39112.25	9781.16
Median Trade Size (EUR)	4705.20	4320.40	9946.44	16748.71	4978.39
Avg Bid-Ask Spread (bps)	6.97	6.85	8.23	3.31	15.20
Median Bid-Ask Spread (bps)	5.44	5.55	4.08	2.90	13.98
Avg Bid-Ask Spread (ticks)	24.44	23.50	34.39	23.51	49.79
Median Bid-Ask Spread (ticks)	20.00	19.00	28.00	14.00	47.00
Observations (N)	17400.00	15891.00	1509.00	884.00	625.00

Table A.15: Summary statistics probit regression data

Summary statistics for all variables used in the Probit regression. All variables are winsorized at the 1% and 99% levels. The statistics are based on 176,112 observations and include: price improvement (in ticks and basis points), order size (in EUR), retail buy dummy, prevailing spread (in ticks and basis points), prevailing order imbalance, same-side imbalance, total prior turnover, prevailing level-1 depth (in EUR), prior realized volatility (in basis points), and price impact (in basis points).

	Price Improve Ticks	Price Improve bps	Order Size (€)	Retail Buy Dummy	Prev. Spread Ticks	Prev. Spread bps
count	176,112	176,112	176,112	176,112	176,112	176,112
mean	1.20	0.89	9.08	0.65	9.29	5.76
std	1.79	1.08	18.21	0.48	11.48	5.03
min	0.00	0.00	0.03	0.00	1.00	0.83
25%	0.00	0.00	0.76	0.00	3.00	2.87
50%	1.00	0.47	2.65	1.00	5.00	4.24
75%	1.00	1.46	9.01	1.00	10.00	7.00
max	12.00	6.05	117.61	1.00	68.00	31.28

	Prev. OIB	Imbal. Same Side	Total Turnover Prior	Prev. L1 Depth (€)	Prior Real. Vol. bps	Price Impact 15s bps
count	176,112	176,112	176,112	176,112	176,112	176,112
mean	0.50	0.47	267.94	336.13	2.60	0.07
std	0.32	0.50	520.87	559.96	3.23	1.96
min	0.00	0.00	0.00	5.79	0.00	-7.41
25%	0.21	0.00	8.38	77.93	0.00	-0.54
50%	0.50	0.00	64.35	174.36	1.66	0.00
75%	0.79	1.00	270.02	357.31	3.46	0.71
max	1.00	1.00	3,142.38	4,037.96	17.78	7.81

Table A.16: Summary statistics OLS regression data

Summary statistics for all variables used in the OLS regression. All variables are winsorized at the 1% and 99% levels. The statistics are based on 122,679 observations and include: price improvement (in ticks and basis points), order size (in EUR), retail buy dummy, prevailing spread (in ticks and basis points), prevailing order imbalance, same-side imbalance, total prior turnover, prevailing level-1 depth (in EUR), prior realized volatility (in basis points), and price impact (in basis points).

	Price Improve Ticks	Price Improve bps	Order Size (€)	Retail Buy Dummy	Prev. Spread Ticks	Prev. Spread bps
count	122,679	122,679	122,679	122,679	122,679	122,679
mean	1.72	1.28	9.90	0.63	10.62	6.30
std	1.92	1.09	19.48	0.48	12.16	5.34
min	0.00	0.00	0.03	0.00	1.00	0.83
25%	1.00	0.44	0.87	0.00	4.00	2.98
50%	1.00	1.11	2.92	1.00	6.00	4.69
75%	2.00	1.66	9.54	1.00	12.00	7.67
max	12.00	6.05	117.61	1.00	68.00	31.28

	Prev. OIB	Imbal. Same Side	Total Turnover Prior	Prev. L1 Depth (€)	Prior Real. Vol. bps	Price Impact 15s bps
count	122,679	122,679	122,679	122,679	122,679	122,679
mean	0.50	0.47	261.62	302.25	2.71	0.05
std	0.32	0.50	529.13	500.83	3.42	2.05
min	0.00	0.00	0.00	5.79	0.00	-7.41
25%	0.21	0.00	6.27	70.94	0.00	-0.60
50%	0.50	0.00	53.76	159.08	1.68	0.00
75%	0.80	1.00	249.31	332.85	3.67	0.71
max	1.00	1.00	3,142.38	4,037.96	17.78	7.81

Appendix B. Market Quality Analysis

Table B.17: Descriptive statistics for ETF market quality variables for Xetra (long-term period)
This table reports summary statistics for the 83-trading-day observation period around the introduction of XR from January 1 to May 31, 2025 (excluding the initial ramp-up phase from March 3 to March 19 and the market turmoil around the U.S. “Liberation Day” from April 2 to April 11) for the 68 analyzed ETFs traded on Xetra. Variables include quoted relative spreads (in basis points), trading activity measures (number of trades, turnover in EUR millions, traded volume in thousands of shares), quoted depth at the best level (Depth_L1) and within 10, 30, and 50 basis points around the midpoint (in EUR thousands), order book imbalance (OBI), and intraday volatility. All variables are computed at the ETF-day level during continuous trading hours.

	Count	Mean	Std	Min	25%	50%	75%	Max
spread	5,644.00	7.27	5.00	0.69	3.97	5.89	9.03	27.29
trades	5,644.00	282.64	436.25	13.00	78.00	158.00	291.00	2,834.71
turnover	5,644.00	4.18	6.49	0.09	1.05	2.16	4.08	38.76
volume	5,644.00	76.13	113.89	1.55	13.70	32.92	80.13	644.68
Depth_L1	5,644.00	253.04	296.81	34.45	107.20	170.19	269.39	1,859.37
Depth_10	5,644.00	2,343.18	3,086.18	32.32	563.89	1,258.27	2,838.75	19,839.25
Depth_30	5,644.00	7,116.97	6,200.95	287.26	2,082.62	5,033.74	10,978.05	26,658.11
Depth_50	5,644.00	9,044.66	6,635.98	588.56	3,456.64	7,566.93	13,304.13	29,359.89
OBI	5,644.00	0.24	0.20	0.00	0.08	0.18	0.35	0.80
volatility	5,644.00	0.11	0.06	0.01	0.07	0.10	0.14	0.30

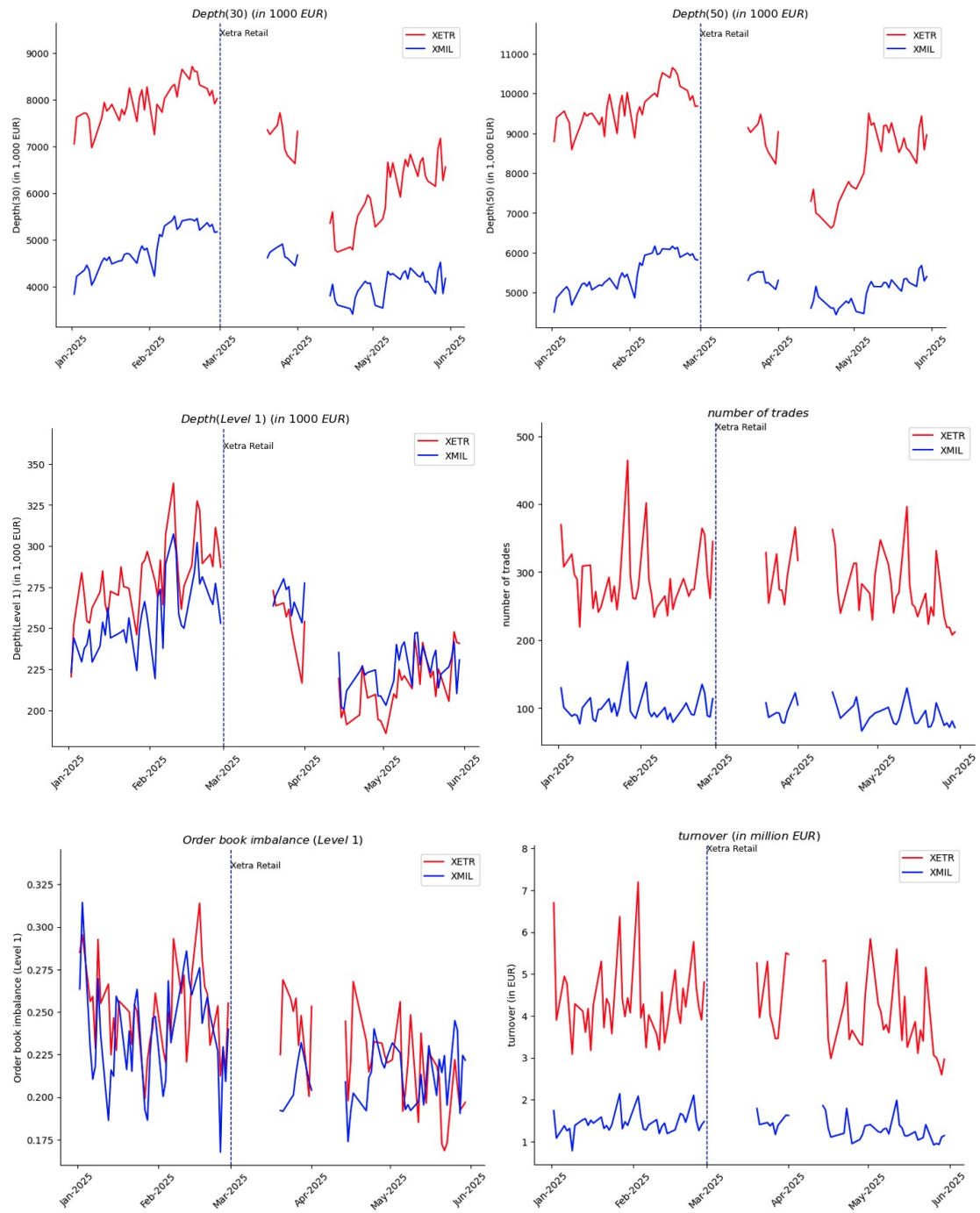


Figure B.5: Average development of remaining market quality variables on Xetra and XMIL around the introduction of XR. The white areas without plotted observations correspond to periods excluded from the analysis, namely the initial ramp-up phase after the introduction of XR for ETFs and the short episode of market turbulence around “Liberation Day”, where abnormal volatility and reduced liquidity conditions could confound the estimation.

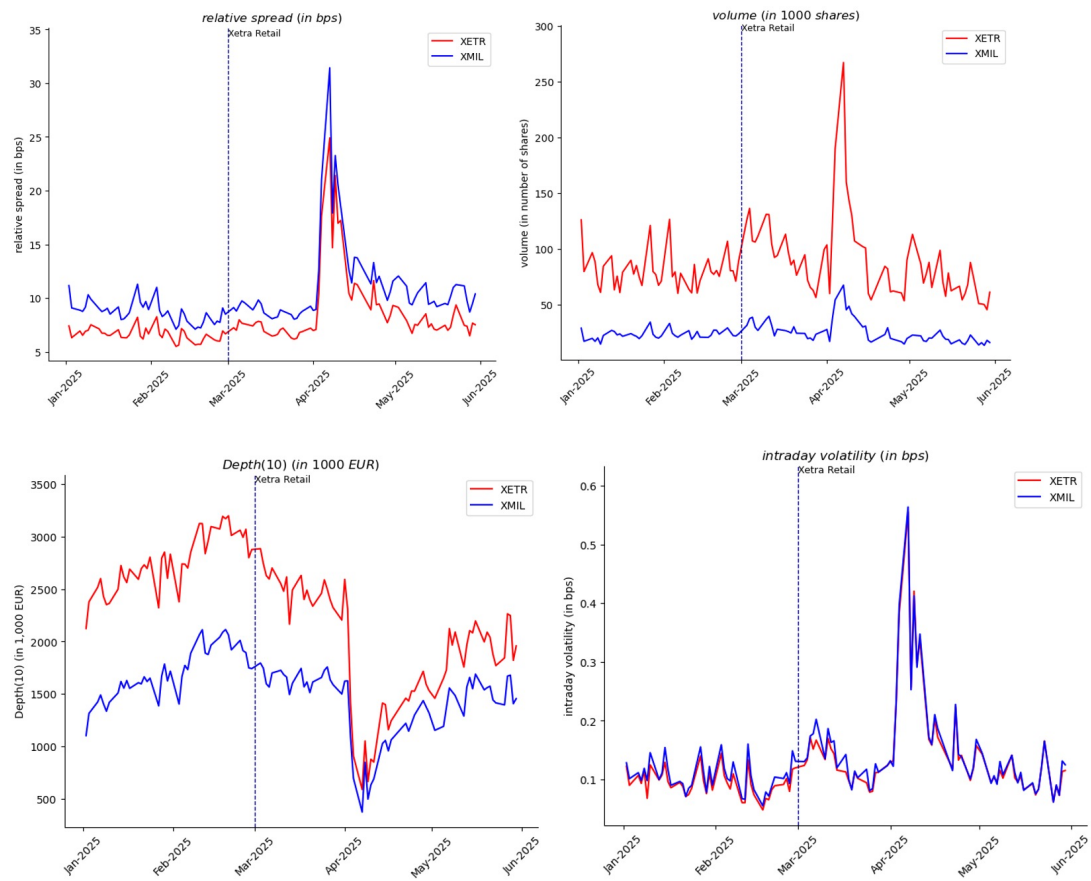


Figure B.6: Average development of major market quality variables on Xetra and XMIL around the introduction of XR. The plot contains the periods excluded from the analysis, namely the initial ramp-up phase after the introduction of XR for ETFs and the short episode of market turbulence around “Liberation Day”, where abnormal volatility and reduced liquidity conditions could confound the estimation.

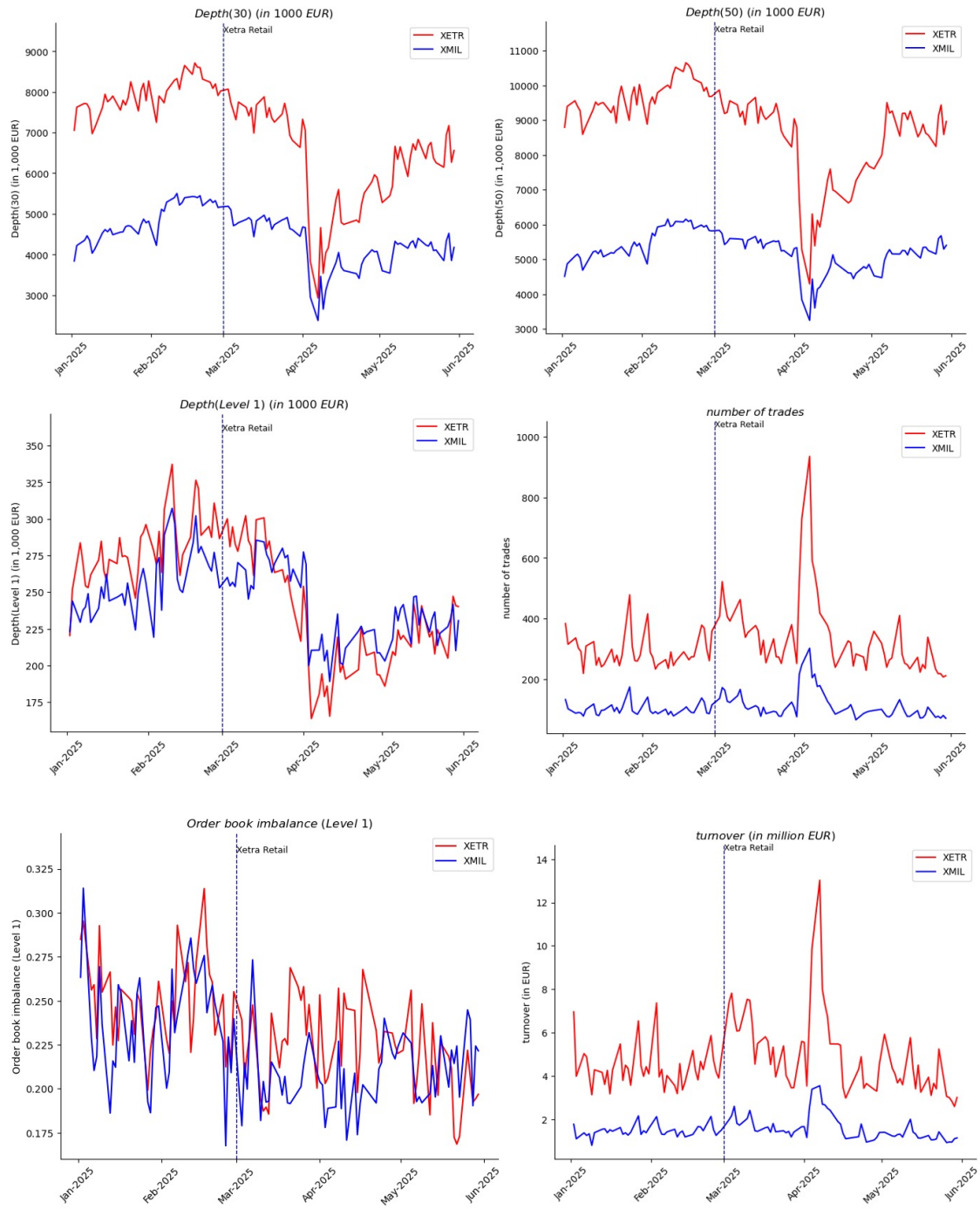


Figure B.7: Average development of remaining market quality variables on Xetra and XMIL around the introduction of XR. The plot contains the periods excluded from the analysis, namely the initial ramp-up phase after the introduction of XR for ETFs and the short episode of market turbulence around “Liberation Day”, where abnormal volatility and reduced liquidity conditions could confound the estimation.

Table B.18: Descriptive statistics for ETF market quality variables for XMIL (long-term period)
This table reports summary statistics for the 83-trading-day observation period around the introduction of XR from January 1 to May 31, 2025 (excluding the initial ramp-up phase from March 3 to March 19 and the market turmoil around the U.S. “Liberation Day” from April 2 to April 11) for the 68 analyzed ETFs traded on XMIL. Variables include quoted relative spreads (in basis points), trading activity measures (number of trades, turnover in EUR millions, traded volume in thousands of shares), quoted depth at the best level (Depth_L1) and within 10, 30, and 50 basis points around the midpoint (in EUR thousands), order book imbalance (OBI), and intraday volatility. All variables are computed at the ETF-day level during continuous trading hours.

	Count	Mean	Std	Min	25%	50%	75%	Max
spread	5,592.00	9.42	7.90	0.87	4.52	7.09	11.01	46.07
trades	5,592.00	95.17	143.33	0.00	24.00	54.00	101.00	844.27
turnover	5,592.00	1.38	2.44	0.00	0.22	0.57	1.39	15.12
volume	5,592.00	21.90	33.92	0.00	3.11	9.38	23.20	189.73
Depth_L1	5,592.00	245.76	176.15	28.31	119.61	203.82	319.77	1,013.34
Depth_10	5,592.00	1,573.35	1,701.80	0.00	492.42	1,026.37	2,099.20	9,274.03
Depth_30	5,592.00	4,516.46	4,188.30	139.52	1,552.26	2,896.59	6,102.03	16,799.59
Depth_50	5,592.00	5,300.59	4,463.81	357.74	2,041.04	3,557.64	7,331.86	18,104.07
OBI	5,592.00	0.23	0.20	0.00	0.08	0.17	0.32	0.85
volatility	5,592.00	0.11	0.07	0.01	0.07	0.10	0.14	0.42

Table B.19: DiD Estimates – Liquidity Measures (Short-Term Analysis)

This table reports coefficient estimates from a DiD panel regression evaluating the effect of the introduction of XR for ETFs on liquidity in the central limit order book on Xetra based on the short-term observation period covering 40 trading days. The dependent variables are the quoted relative spread (in basis points) and displayed depth at the best level (Depth_L1) and within 10, 30, and 50 basis points of the midpoint (in EUR thousands). The $Treat \times Post$ interaction identifies the average treatment effect of the XR launch for ETFs listed on Xetra relative to the same ETFs on Euronext Milan. All regressions include ETF and day fixed effects and control for volatility, inverse price, turnover, and spread (except when the spread is the dependent variable). Standard errors are double-clustered by ETF and trading day. Statistical significance is denoted by $*p < 0.1$, $**p < 0.05$, and $***p < 0.01$.

	spread	Depth_L1	Depth_10	Depth_30	Depth_50
Treat x Post	-0.0544 (-0.3100)	-34.675*** (-3.9404)	-554.36*** (-5.5620)	-944.39*** (-3.4848)	-1073.9*** (-3.3948)
Treat	-0.1350 (-0.4827)	-6.8373 (-0.3259)	915.26*** (3.1105)	2667.6*** (5.3586)	3822.2*** (7.2410)
turnover	-1.0684*** (-5.0310)	23.318** (2.5243)	161.08* (1.6739)	270.13* (1.8435)	308.22* (1.8748)
inv_price	108.29* (1.7270)	-719.08 (-0.4849)	2.954e+04** (2.1099)	7.539e+04*** (2.8774)	3.016e+04 (1.3097)
volatility	21.829*** (6.3664)	-231.36*** (-4.3576)	-1800.4*** (-2.5833)	-6326.5*** (-3.5353)	-6103.9*** (-3.6245)
spread		3.5316** (2.0997)	31.408** (2.1788)	72.570** (2.2115)	94.279*** (2.7793)
Entity FE	yes	yes	yes	yes	yes
Day FE	yes	yes	yes	yes	yes
No. Observations	5355	5355	5355	5355	5355
R-Squared (Within)	0.4029	0.0444	0.1479	0.2468	0.3674

Table B.20: DiD Estimates – Trading Activity, Order Imbalance, and Volatility (Short-Term Analysis)

This table reports coefficient estimates from a DiD panel regression evaluating the effect of the introduction of XR for ETFs on trading activity and price dynamics based on the short-term observation period covering 40 trading days. The dependent variables are order-book imbalance at the first order book level (OBI), number of trades, turnover (EUR millions), traded volume (in thousands of shares), and intraday volatility (in basis points). The $Treat \times Post$ interaction identifies the average treatment effect of the XR launch for ETFs listed on Xetra relative to the same ETFs on Euronext Milan. All regressions include ETF and day fixed effects and control for volatility, inverse price, spread, Depth_L1 (except when OBI is the dependent variable), and turnover (except when the a trading activity measure is the dependent variable). Standard errors are double-clustered by ETF and trading day. Statistical significance is denoted by $*p < 0.1$, $**p < 0.05$, and $***p < 0.01$.

	OBI	trades	turnover	volume	volatility
Treat x Post	0.0191 (1.3457)	0.0146 (0.3799)	0.0375 (0.7059)	0.0330 (0.6138)	0.0050 (1.1541)
Treat	0.0050 (0.2848)	1.0727*** (10.294)	1.2207*** (11.227)	1.2252*** (11.219)	-0.0093** (-2.4346)
turnover	-0.0041 (-0.7410)				0.0059*** (4.7152)
spread	-0.0034** (-2.0588)	-0.0751*** (-4.4887)	-0.1071*** (-6.6376)	-0.1072*** (-6.6756)	0.0057*** (5.7335)
inv_price	-0.1015 (-0.0468)	-0.3149 (-0.0517)	-0.5773 (-0.0682)	5.7119 (0.6710)	0.5626 (1.0241)
volatility	0.0281 (0.4548)	1.9179*** (4.7129)	2.2195*** (4.6148)	2.4113*** (4.8247)	
Depth_L1		9.795e-05 (0.3220)	0.0007*** (2.9441)	0.0007*** (2.7771)	-1.824e-05** (-2.4566)
Entity FE	yes	yes	yes	yes	yes
Day FE	yes	yes	yes	yes	yes
No. Observations	5355	5355	5355	5355	5355
R-Squared (Within)	0.0046	0.5491	0.4744	0.4714	0.2737