RFQ Dominance and Lit Trading in European ETFs: Peaceful Coexistence?*

Jérôme Dugast† Thomas Marta‡ Fabrice Riva§

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Abstract

We study Request-for-Quote (RFQ) trading in European ETF markets, where RFQs account for the majority of volume. Using granular trade-level data, we compare RFQs to lit executions through a spread decomposition framework. Price impact is consistently lower for RFQ trades, a result that holds under entropy balancing and matched-sample analyses. While price impact for lit trades increases with trade imbalance, RFQ executions are less sensitive to prevailing order flow. We also document a strong association between RFQ activity and ETF primary market flows. RFQs are widely used for institutional-sized execution with limited market impact and information leakage.

JEL classification: G14, G15, G23

Keywords: Request-for-Quote (RFQ), Exchange-Traded Funds (ETFs), market structure, trading costs, price impact, primary market activity, liquidity.

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†ESSEC Business School

‡Wilfrid Laurier University – Lazaridis School of Business and Economics

§Université Paris Dauphine - PSL

1 Introduction

In this paper, we investigate Exchange-Traded Fund (ETF) trading in Europe, with a focus on the dominant trading mechanisms and their implications for market dynamics. We find that in 2024, 57.5% of the main ETFs' trading volume in the European market is executed on two major dark pan-European trading platforms, Tradeweb and Bloomberg, via Request-for-Quotes (RFQs). In contrast, lit venues account for a smaller share of trading volume, with Xetra dominating with only 12.6% of the trading volume, while other dark venues such as dark pools are negligible.

The widespread use of RFQs brings to the forefront a longstanding debate in the literature on the trade-off between transparency and execution quality. Lit markets, by design, promote price discovery through visible order flow and competitive quoting (Hasbrouck (1991)), but this transparency can expose large traders to information leakage and higher market impact costs (Easley, Kiefer, and O'Hara (1996)). Mechanisms designed to accommodate large orders—such as upstairs markets, block trading, or dark pools—can mitigate these frictions by reducing order flow transparency, but may come at the cost of diminished price discovery when too much trading is diverted away from lit venues (Bessembinder and Venkataraman (2010), Zhu (2014), Anand, Samadi, Sokobin, and Venkataraman (2021)). The net effect of RFQs on market quality, therefore, is ambiguous: they may enhance execution for large orders, as suggested by the block trading literature (Madhavan (1995), Keim and Madhavan (1997)), or they may undermine transparency and competition if they displace lit liquidity. Whether RFQs complement or substitute lit trading remains an open empirical issue.

In this context, this paper addresses five key questions. First, are RFQ prices competitive relative to prevailing market prices? Second, are RFQs informed, in the sense that they convey or reflect private information? Third, what are the determinants of RFQ usage in the European ETF market? Fourth, what is the impact of RFQ activity on ETF primary market dynamics, particularly creation and redemption flows? Fifth, do RFQs exert a substitution effect that deteriorates the liquidity of lit markets, or do they play a complementary role that supports the coexistence of trading mechanisms?

To address these questions, we first analyze the transaction cost structure of RFQ and lit market trades, decomposing costs into effective spread, realized spread, and price impact. Our analysis uses a proprietary dataset from BMLL, from which we construct a sample of 90 ETFs selected for liquidity and representativeness. We document a segmented trading landscape: while the vast majority of trades occur on lit venues, the bulk of trading volume is executed via RFQs, reflecting the size concentration of institutional orders.

Next, to formally assess how trading costs vary with execution mechanism, we estimate panel regressions of effective spread, realized spread, and price impact on an RFQ indicator, controlling for trade size and other relevant factors. By including ETF, date, and time fixed effects, the regressions account for differences in asset characteristics and market conditions that could confound cross-venue comparisons. The results show that price impact is consistently lower for RFQ trades than for lit market trades.

To further investigate the counterfactual in which a large trade is split into smaller child orders executed sequentially on lit venues, we use trade imbalance as a proxy for preceding order flow and directional pressure. Price impact increases with trade imbalance for lit trades but remains largely unchanged for RFQ executions. This pattern suggests that, relative to lit trading, RFQ executions are less sensitive to prevailing order flow and may help avoid the cumulative market impact typically associated with order splitting. By concentrating execution at a single point in time, RFQs appear to be associated with lower price pressure and reduced sensitivity to directional flow, particularly for larger trades.

The result that price impact is lower for RFQ trades remains robust across a wide range of tests. It holds under alternative measurement windows, pre-trade timing assumptions, trade sizes, ETF asset classes, and liquidity tiers. Although price impact remains consistently lower for RFQ executions relative to lit trades, the effective spread varies with ETF characteristics and trade size.

To further address potential selection bias in execution mechanism choice—particularly with respect to trade size—we implement two complementary identification strategies: entropy balancing and matched-sample analysis. The entropy balancing procedure reweights lit trades so that, within each ETF and trade-direction group, the weighted distribution of trade size exactly matches that of RFQ trades. To avoid imbalances that could bias comparisons, we restrict the sample to ETF-direction pairs with sufficient overlap in execution types. The matched-sample analysis complements this strategy by applying exact matching on ETF, trading day, and trade direction, and nearest-neighbor Mahalanobis matching on trade size, restricting the analysis to highly similar trades. While both approaches reduce sample size—albeit in different and complementary ways—they yield well-balanced comparison groups. In both cases, price impact remains significantly lower for RFQ trades, suggesting that the observed differences are unlikely to be driven by selection into execution mechanism.

We then examine the relation between RFQs and the ETF primary market. Using ETF-day panel regressions, we document a strong, persistent positive association between

RFQ activity and the notional value of primary market activity by authorized participants (APs). Given that the primary market involves large transactions (via creation units of 25,000–100,000 shares), and that RFQs are empirically linked to large trades, our findings suggest that RFQs function as a key execution mechanism through which institutional trading demand initiates supply adjustments via the creation and redemption process. Dynamic models show RFQ activity precedes and predicts primary flows, reinforcing this interpretation. Notably, the effect is not driven by arbitrage: RFQ volume is unrelated to mispricing, while primary flows are. These results suggest RFQs accommodate uninformed institutional liquidity demand, while the creation/redemption process facilitates ETF inventory adjustments, supporting liquidity and price efficiency.

Finally, we test whether RFQ activity interacts with lit market conditions in a substitutive or complementary way. Using a panel regression at the ETF-day level, we regress RFQ volume on lagged, contemporaneous, and lead measures of lit market liquidity, including volume, volatility, quoted spreads, and depth. We find that RFQs are most strongly associated with lit market volume on high-RFQ days: medium and large RFQs tend to occur when lit volume is elevated and are followed by narrower spreads. These results suggest that RFQs do not drain liquidity from lit venues but instead coexist with, and may even reinforce lit market quality.

We contribute to the market structure and ETF intermediation literature by documenting that price impact is lower for RFQ trades than for lit trades. This pattern reflects the role of RFQs in providing immediate liquidity with limited information leakage. RFQ trades exhibit modest price impact that does not increase with trade imbalance, unlike lit executions. We also find a strong association between RFQ activity and ETF primary market flows, suggesting that RFQs serve as a key channel for institutional demand linked to creations and redemptions. Finally, RFQ usage is concentrated in specific environments but is not associated with deteriorating lit market quality: volatility, spreads, and depth remain stable, and lit trade volumes increase on high-RFQ days. These findings contribute to the literature on large-order execution by showing that RFQs accommodate such trades without impairing lit market conditions and with limited price impact.

The rest of the paper is organized as follows. Section 2 reviews the literature on market structure, trading mechanisms, and ETF intermediation. Sections 3 and 4 analyze the implicit transaction costs of trades executed on lit markets versus RFQs and present robustness checks. Section 5 addresses potential selection bias in execution mechanism choice using entropy balancing and nearest-neighbor matching. Section 6 investigates the link between RFQs and ETF creation and redemption flows. Section 7 assesses whether RFQs substitute for or complement lit market activity. Section 8 concludes.

2 Literature Review

This paper contributes to several strands of literature on market structure, trading mechanisms, and ETF intermediation. Our primary contribution relates to the literature on the interplay between lit markets, large-order execution, block trading, and dark execution. Lit venues facilitate price discovery through transparent and competitive quoting, but such transparency can expose large traders to information leakage and adverse market impact. Hasbrouck (1991) highlights the benefits of transparency for price informativeness, whereas Easley, Kiefer, and O'Hara (1996) show that it can increase execution costs for informed or large traders.

Alternative trading mechanisms—such as upstairs markets, block trading, and, more recently, dark pools—have emerged to accommodate large orders while mitigating these frictions. Madhavan (1995) and Keim and Madhavan (1997) show that large trades can achieve lower market impact and better execution quality when shielded from public order flow. However, overreliance on non-transparent venues may undermine market quality. Bessembinder and Venkataraman (2010) find that shifting substantial order flow away from lit markets weakens price discovery. Zhu (2014) and Anand, Samadi, Sokobin, and Venkataraman (2021) echo this concern in the context of dark pools, documenting that while dark trading can improve execution for large trades, excessive dark activity may harm liquidity and impair informational efficiency. Nevertheless, dark and lit venues can coexist productively when they serve distinct trading needs, as shown in Comerton-Forde, Malinova, and Park (2018).

We build on this literature by examining RFQs as a distinct execution mechanism in the European ETF market. While RFQs share features with both block trading and dark venues—such as limited pre-trade transparency and the ability to execute large trades—they differ in their non-anonymous, quote-based format, in which clients request prices from selected market participants. This makes them operationally and strategically distinct. Our analysis shows that RFQs divert significant order flow away from lit venues, consistent with concerns raised in Bessembinder and Venkataraman (2010). However, we find no systematic evidence of market quality deterioration. Instead, RFQ activity is positively associated with lit market volume and exhibits significantly lower price impact, even for medium and large trades. This is consistent with Madhavan (1995) who emphasizes the role of block trading in mitigating adverse selection costs. Moreover, we document that the interaction between RFQs and lit markets varies with market structure: RFQs dominate in environments where they improve execution costs, while lit venues remain competitive for small-sized trades in more balanced settings, extending insights from Comerton-Forde, Malinova, and Park (2018).

Our study also contributes to the growing literature on the ETF primary market and intermediation process (Pan and Zeng (2016); Fulkerson, Jordan, and Travis (2022); Gorbatikov and Sikorskaya (2021); Zurowska (2022)). While prior work focuses on the pricing efficiency and arbitrage mechanisms of ETFs, we are the first to examine how institutional size trading via RFQs relates to primary market flows. We show that RFQ volume is strongly associated with the ETF primary market, even after controlling for mispricing and liquidity conditions. This relation is persistent and predictive, suggesting that RFQs serve as the primary execution route through which APs satisfy institutional demand. Furthermore, RFQs appear largely uninformed: they exhibit low price impact relative to transaction costs and show no strong relation to mispricing. These findings position RFQs as a central but previously unexamined component of ETF market microstructure in Europe, enabling the execution of institutional-size orders while limiting information leakage and adverse price impact, and maintaining overall transaction costs at competitive levels.

3 RFQs and Lit Markets: A Spread Decomposition Approach

3.1 Data

The analysis draws on a proprietary dataset from BMLL Technologies. To ensure representativeness and tractability, we apply two filters to our ETF sample: (1) a minimum average daily trading volume exceeding €1 million during the first 180 days of 2024, and (2) assets under management (AUM) above €100 million. Our main sample covers 90 ETFs. The sample period spans from September 2021 to January 2025.[1]

ETFs in Europe are traded across multiple venues and often in several currencies per venue. Table IA1 lists the European trading venues in our sample, identified by their MIC codes, for which we obtain access through BMLL. To illustrate the relative importance of these venues, Figure 2 reports total ETF trading volumes for the main venues. RFQ platforms—namely Bloomberg (BMTF) and Tradeweb (TWEN)—account for 56.5% of trading volume over the sample period from September 2021 to January 2025. Trading volume is highly concentrated: the 8th venue in our 20-venue sample accounts for only 1.6% of total trading activity.

For simplicity, we focus on RFQs and the primary lit venue of each ETF in its main trading currency. Given the strong concentration of volume in these venues and currencies, we exploit this structure to streamline the analysis. This approach also mitigates potential noise from currency effects that could bias the results. At the trade-level granularity con-

[1] We have access to some data up to January 2018, but for Bloomberg RFQs, coverage begins in September 2021.

sidered in this section, RFQ executions on Bloomberg are not observable; accordingly, we include only RFQs executed on Tradeweb.

3.2 Spread Decomposition

We begin by analyzing spread-related trading costs using a standard spread decomposition, which separates the effective spread into the realized spread and price impact.

$$\underbrace{2q_t(p_t - m_t)}_{\mathit{EffSpread}} = \underbrace{2q_t(p_t - m_{t+\Delta})}_{\mathit{RSpread}} + \underbrace{2q_t(m_{t+\Delta} - m_t)}_{\mathit{PImpact}}, \quad \Delta = 60 \text{ seconds}, \tag{1}$$

where p_t is the execution price, m_t is the prevailing midquote at the time of the trade, $m_{t+\Delta}$ is the midquote one minute later,[2] and $q_t \in \{-1, 1\}$ denotes trade direction (-1 for seller-initiated trades, $+1$ for buyer-initiated trades). The effective spread measures the total cost of immediacy. The realized spread captures liquidity provider revenue, including order processing and inventory costs. The price impact reflects permanent price movements associated with adverse selection or information effects. For lit trades, trade direction is directly available in the BMLL database. For RFQ trades, direction is inferred based on whether the execution price is above or below the prevailing midquote, under the assumption that RFQs do not receive price improvement.

[2] We also test a Δ of 20 minutes in the robustness section with results presented in Table IA2.

3.3 Descriptive statistics

Table 2 presents summary statistics on the spread decomposition by trade size and execution mechanism. The data reveal distinct patterns in both cost structures and venue usage.

First, we observe sharp segmentation by trade size across execution mechanisms. Lit markets are predominantly used for small transactions, while RFQs serve as the primary venue for institutional-sized trading. Over the sample period, we record about 14 million small lit trades (notional under €1 million) compared with roughly 460,000 small RFQs. Conversely, there are 10,416 large RFQ trades (notional above €3 million) but only 586 large lit trades. This imbalance highlights the specialization of trading mechanisms by trade size and execution objectives.

Second, trades executed via RFQ tend to have substantially lower price impact, averaging around 1 basis point across trade sizes. The difference in *PImpact* between RFQ and lit-venue execution is especially pronounced. For small trades, RFQ executions exhibit an average *PImpact* of 0.4 basis points, compared with 3.8 basis points for lit-venue trades. Even for medium trades, RFQs maintain a low price impact (0.5 bps vs. 3.4 bps), and for large trades, the impact remains under 1 bps. The scarcity of large lit trades complicates direct comparisons in that segment, but the 3.8 bps average price impact for small lit trades suggests that splitting a large order across multiple small lit executions would generate cumulative market impact exceeding the effective spread of an equivalent large order executed via RFQ. Hence, even without many large lit observations, the summary statistics provide a clear economic rationale for RFQ usage.

These patterns are illustrated in Figure 1, which reports average effective spread, realized spread, and price impact across trade-size bins and execution mechanisms, underscoring both the segmentation of trading activity and the contrasting cost components of RFQ and lit execution.

3.4 Empirical approach

To formally assess the relation between trade execution method and the components of transaction costs, we estimate the following specification for each trade:

$$Y_{it} = \alpha_i + \beta \cdot \mathbb{1}_{RFQ,it} + \gamma \cdot \text{TradeSize}_{it} + \delta \cdot \text{Buy}_{it} + \lambda_t + \theta_h + \varepsilon_{it}, \tag{2}$$

where Y_{it} denotes one of the three dependent variables: *EffSpread*, *RSpread*, or *PImpact*, for trade i on day t. The indicator variable $\mathbb{1}_{RFQ,it}$ equals one if the trade was executed via RFQ. The variable TradeSize_{it} captures the notional value of the trade (in log euros), and Buy_{it} is an indicator equal to one for buyer-initiated trades. We include ETF fixed effects (α_i) to control for time-invariant differences across ETFs, day fixed effects (λ_t) to absorb daily market-wide variation in liquidity conditions, and 30-minute time-bin fixed effects (θ_h) to account for predictable intraday liquidity patterns. Each trade is assigned to a time bin based on its execution timestamp. Standard errors are clustered at the ETF and day levels.

3.5 Results

Table 3 presents coefficient estimates from regressions of *EffSpread*, *RSpread*, and *PImpact* on an RFQ indicator, controlling for trade size, trade direction, and ETF, date, and time bin fixed effects. In line with Madhavan (1995), price impact is lower for RFQ trades: the coefficient on $\mathbb{1}_{RFQ}$ is -2.02 basis points (standard error 0.18), statistically significant at the 1% level. This indicates that, conditional on trade size and other controls, RFQ trades incur lower market impact than comparable lit-venue trades.

In addition, effective spreads are lower and realized spreads are higher for RFQ trades. The realized spread coefficient is positive and significant (1.59 basis points), indicating that liquidity providers earn greater revenues on RFQ executions relative to lit trades. This pattern is consistent with lower information asymmetry and reduced adverse selection in RFQ transactions. The negative coefficient on *EffSpread* reflects lower quoted execution costs for RFQs on average.

3.6 Trade Imbalance Interaction

Next, we further test the hypothesis that RFQs reduce total execution costs by shielding institutional trades from the cumulative market impact associated with slicing large orders into multiple child trades executed sequentially on lit venues. In such settings, order splitting may produce persistent trade imbalances, gradually revealing directional intent and moving prices through a combination of information leakage and mechanical price pressure. By contrast, RFQs provide a single-point execution mechanism that reduces execution uncertainty, limits information dissemination, and mitigates adverse price impact.

To examine this hypothesis, we estimate regressions that interact $\mathbb{1}_{RFQ}$ with a measure of recent trade imbalance, *TI30A*, defined as the signed logarithm of net order flow over the preceding 30 minutes. A positive value of *TI30A* indicates that recent trades were predominantly in the same direction as the current trade, amplifying the likelihood of information leakage and price pressure. The interaction term $\mathbb{1}_{RFQ} \times TI30A$, therefore, captures how the execution cost of RFQ trades responds to directional order flow, relative to lit executions.

Table 4 reports regression results that examine how execution costs vary with recent trade imbalance. In the absence of the interaction term, the coefficient on *TI30A* captures the sensitivity of lit-market trades to prevailing directional flow. Consistent with prior work on order imbalance and price pressure (Chordia, Roll, and Subrahmanyam, 2002), price impact increases with trade imbalance for lit executions: the coefficient on *TI30A* in the *PImpact* regression is 0.05 (standard error 0.01, $p < 0.01$), indicating that lit trades incur higher market impact when executed in the direction of recent flow.

By contrast, the interaction term $\mathbb{1}_{RFQ} \times \log(\textit{TI30A})$ is negative and statistically significant in the *PImpact* regression ($\beta = -0.04$, $p < 0.01$), indicating that price impact is less responsive to trade imbalances for RFQ executions than for lit trades. This attenuated sensitivity suggests that RFQ trades are less exposed to the path-dependent execution costs observed on lit venues.

The coefficient on $\mathbb{1}_{RFQ}$ remains consistent with our main specification: price impact is significantly lower for RFQ trades (-1.90 bps), realized spreads are higher (1.46 bps), and effective spreads are modestly lower (-0.60 bps), reinforcing the robustness of our core results. For both *EffSpread* and *RSpread*, the interaction terms $\mathbb{1}_{RFQ} \times \log(\textit{TI30A})$ are positive and statistically significant, though economically small relative to the main effects. Taken together, these estimates continue to support a cost advantage for RFQs in terms of total execution costs.

These results support the interpretation that RFQs are used strategically to mitigate information leakage and avoid the cumulative market impact associated with order splitting. By enabling a single, negotiated execution, RFQs allow institutions to access liquidity without signaling their trading intentions, thereby minimizing both price pressure and total execution costs.

4 Robustness

4.1 Robustness to Alternative Time Interval

To further evaluate the robustness of our spread decomposition results, we extend the measurement window for realized spread and price impact, Δ, from 60 seconds to 20 minutes. This longer horizon accounts for the possibility that market reactions to RFQs may be delayed. In addition, while most RFQs are disclosed promptly—in our sample, 98% are published within one minute—transactions exceeding the large-in-scale (LIS) thresholds may be subject to publication deferrals, with the duration determined by the relevant national competent authority.[3] If market participants adjust their quotes with a delay, or only after deferred publication, the baseline 60-second window may understate the full price impact of RFQ execution. The corresponding regression results are presented in Table IA2. The results remain qualitatively unchanged, confirming that our main findings are robust to the choice of Δ.

[3] European Commission, *Regulatory Technical Standards (RTS 1) under MiFID II*, July 2016. Available at `https://ec.europa.eu/finance/securities/docs/isd/mifid/rts/160714-rts-1_en.pdf`. The main results are robust to excluding trades published more than one minute after execution; see Table IA3.

4.2 Robustness to Pre-Trade

To further assess the timing of market reactions, we introduce an alternative price impact measure pre-trade, *PImpact_PT*, which computes the 20-minute price impact using the midpoint observed three minutes before execution for RFQs. This specification accounts for potential market movements between the initiation of the RFQ process and execution. The results, reported in the fourth column of Table IA2, are consistent with our main findings: price impact remains lower for RFQ trades than for lit trades. This pattern does not appear to be driven by dealers adjusting quotes between the start of the RFQ process and execution, a timing effect that would not be captured in our baseline specification. These results provide further evidence that market impact remains consistently lower for RFQ trades than for lit executions.

4.3 Robustness Across Asset Class and Liquidity

To assess the robustness of our baseline findings, we re-estimate the main specification across three subsamples: (i) the top tercile of ETFs by trading volume, (ii) equity ETFs, and (iii) fixed income ETFs. These cuts help evaluate potential heterogeneity in execution costs across asset classes and liquidity tiers. Figure 3 displays trading volume by asset class and venue, showing that RFQs dominate not only in fixed income ETFs—where they account for 83% of volume—but also play a significant role in equity ETFs.

Top Tercile by Trading Volume (Panel A of Table IA4). In the most actively traded ETFs, price impact is significantly lower for RFQ trades (-1.61 basis points, $p < 0.01$), while the coefficient on *EffSpread* is negative but not statistically significant. These results indicate that price impact remains lower for RFQ executions even in highly liquid instruments. In a robustness check limited to the five most active ETFs (Table IA5), where ETF fixed effects are omitted, effective spreads and price impact are also significantly lower for trades executed via RFQ.

Equity ETFs (Panel B of Table IA4). In the equity ETF subsample, price impact is 1.99 basis points lower for RFQ trades ($p < 0.01$), consistent with the main sample.

Fixed Income ETFs (Panel C of Table IA4). In fixed income ETFs, the difference is even larger: price impact is 2.45 basis points lower for RFQ trades ($p < 0.01$), which may reflect lower baseline liquidity and a greater reliance on large size execution in this segment.

Across all three subsamples—high-turnover ETFs, equity ETFs, and fixed income ETFs—price impact remains significantly lower for trades executed via RFQ. This robustness supports the view that total execution costs are lower for RFQ trades, reflecting reduced exposure to the cumulative market pressure typical of lit-venue trading.

4.4 Robustness Across Trade Size

To assess whether the relation between execution method and transaction costs varies across the trade size distribution, we estimate the regression specification separately for small, medium, and large trades. Table IA6 reports the coefficient estimates for each cost component.

Consistent with the main specification, price impact is significantly lower for RFQ trades across all size bins. The coefficient on $\mathbb{1}_{RFQ}$ in the *PImpact* regression is -2.011 basis points for small trades, -3.521 for medium trades, and -4.024 for large trades—all statistically significant at the 1% level. These estimates indicate that the lower market impact associated with RFQ executions persists across trade sizes, including large transactions.

The trade-off across cost components, however, differs by size category. For medium and large trades, effective spreads and realized spreads are significantly higher for RFQ trades. For example, in the large trade bin, the coefficient on $\mathbb{1}_{RFQ}$ is 2.723 basis points for *EffSpread* and 7.854 basis points for *RSpread*, both significant at the 1% level. These estimates should be interpreted with caution, given the relatively small number of observations in the large trade bin (11,002 observations, of which 10,416 are RFQs and only 586 are lit trades). In contrast, for small trades, effective spreads are significantly lower for RFQ trades (-0.679 basis points, $p < 0.01$), suggesting that bilateral negotiation may support tighter pricing in this segment.

Overall, the results highlight a spread–impact trade-off across trade sizes: price impact is consistently lower for RFQ trades, while quoted and realized spreads are generally higher for medium and large trades. Small trades are the exception, with both price impact and effective spreads lower for RFQ executions. The magnitude and statistical significance of the price impact coefficients across all bins underscore the robustness of this relation. These patterns are consistent with the idea that RFQs help reduce total execution costs by limiting the market pressure associated with order splitting on lit venues.

4.5 Robustness to Absolute Value of the Spread Decomposition

While for lit trades, BMLL indicates the direction of the aggressor, for RFQ trades, trade direction is not reported and must be inferred based on whether the execution price is above or below the prevailing midquote. This imputation may introduce bias into the spread decomposition. To assess the robustness of our results to this assumption, we re-estimate the main specification using the absolute values of the spread decomposition. Indeed, using absolute values mitigates potential bias from misclassifying trade direction. The results are presented in Table IA7. Confirming our main findings, absolute price impact ($|PImpact|$) is lower for RFQ trades, with a coefficient of -1.22, significant at the 1% level.[4]

4.6 Overall

Across all robustness checks, price impact remains significantly lower for RFQ trades relative to lit trades. This consistent pattern supports the view that market impact is lower for RFQ executions, particularly for institutional-sized transactions. By contrast, the higher price impact observed for lit trades is consistent with their role in price discovery and information incorporation.

5 Addressing Selection Bias in Execution Mechanism Choice

To mitigate potential endogeneity in the choice between RFQ and lit execution, we implement two complementary identification strategies. First, we use entropy balancing to reweight control observations such that their covariate distribution matches that of RFQ trades. Second, we perform a nearest-neighbor matching procedure based on trade characteristics

[4]However, unlike the main specification, absolute realized spread ($|RSpread|$) is also significantly lower for RFQ trades in this specification. This pattern suggests that the higher $RSpread$ observed for RFQs in the main results may be partly influenced by trade direction misclassification.

and timing. Both approaches isolate the effect of the execution mechanism on transaction costs by ensuring that the comparison between RFQ and lit trades is made under comparable market conditions.

5.1 Entropy Balancing on Trade Characteristics

Entropy balancing reweights lit trades so that, within each ETF and trade-direction group, the weighted means of trade-level size exactly match those of the RFQ trades. Specifically, we partition the sample by ETF and trade direction ($\mathbb{1}_{Buy}$) and, within each subset, estimate entropy-balancing weights on *TradeSize*. This procedure ensures that, for every ETF and trading side, the weighted distribution of trade size among lit trades mirrors that of RFQ trades. We restrict the sample to ETFs and trading sides (buy/sell) that exhibit sufficient overlap in execution mechanisms—specifically, we retain only groups in which both RFQ and lit trades represent at least 2% of total observations.[5]. This procedure ensures that, for every ETF and trading side with adequate overlap, the weighted distribution of trade size among lit trades mirrors that of RFQ trades.

The regressions are then estimated using these entropy-balancing weights, with fixed effects for trading day, ETF, and 30-minute time bins. This specification isolates variation in execution mechanism while preserving comparability in trade characteristics both across and within ETFs. Unlike unweighted OLS, entropy balancing achieves exact covariate balance on observables, though it necessarily excludes ETFs with no overlap between execution types.

Regression results for the entropy-balanced sample are reported in Table 5. Even after

[5] This filtering step avoids degenerate cases where one execution mechanism dominates an ETF, ensuring feasible reweighting and matching.

enforcing exact covariate balance on trade size, price impact remains substantially lower for RFQ trades, with an estimated coefficient of -1.93 basis points, statistically significant at the 1% level. For effective spread, the coefficient on $\mathbb{1}_{\text{RFQ}}$ is negative (-0.31 basis points) but not statistically significant, indicating that total trading costs for RFQ and lit executions are broadly comparable once trade characteristics are balanced.

5.2 Matching on Trade Characteristics

To further address potential selection bias, we implement a nearest-neighbor matching procedure that pairs RFQ and lit trades of the same ETF, trading day, and trade direction, based on their trade size. As in the entropy-balancing approach, we first restrict the sample to ETFs and sides with at least 2% representation of both RFQ and lit trades to ensure sufficient overlap. We then perform Mahalanobis matching on *TradeSize*, with exact matching on ETF (*Lid*), trading day (*Date_id*), and trade direction ($\mathbb{1}_{Buy}$). This procedure ensures that matched trades occur under identical information environments—same ETF, day, and side—and are comparable in size, thereby minimizing selection effects due to market conditions or trade timing.[6]

Regression results based on the matched sample are presented in Table 6. Price impact remains significantly lower for RFQ trades (-1.91 basis points, significant at the 1% level), even when trades are matched within the same ETF, day, and trade direction. Realized spreads remain higher for RFQ trades (1.40 basis points, significant at the 1% level), indicating greater revenue retention by liquidity providers. Effective spreads are also significantly

[6] Because the matching is exact on ETF and day, and nearest-neighbor on size, the number of observations decreases from approximately 15 million to 0.85 million trades.

lower for RFQ trades (-0.68 basis points).

Taken together, these results are consistent with the entropy-balanced analysis: price impact is markedly lower for RFQ trades without a corresponding increase in other transaction costs. This pattern suggests that market impact is lower on RFQ venues, while execution quality remains broadly comparable to that of lit markets.

6 ETF Primary Market Activity and RFQs

6.1 Empirical Approach

Next, we turn to the relation between RFQ activity and ETF primary market flows. Since the ETF primary market operates at a daily frequency, we move to ETF-day-level granularity. At this granularity—unlike in the previous section—we also observe RFQ executions on Bloomberg.

We regress the log of the absolute notional value of daily creations and redemptions, denoted $logCR_{it}$, on the log of total RFQ volume ($logRFQ_{it}$) and a set of ETF-level controls. Specifically, we estimate:

$$\begin{aligned} logCR_{it} = \beta_1 \cdot logRFQ_{it} + \beta_2 \cdot |Mis_{it}| + \beta_3 \cdot logLit_{it} + \beta_4 \cdot Volat_{it} \\ + \beta_5 \cdot BASpread_{it} + \beta_6 \cdot Depth_{it} + \alpha_i + \lambda_t + \varepsilon_{it} \end{aligned} \tag{3}$$

where i indexes ETFs and t indexes days. The control variables capture known determinants of primary market activity, including ETF mispricing, lit market volume, intraday volatility, quoted spread, and order book depth. Both $logCR_{it}$ and $logRFQ_{it}$ are computed as log-transformations of their raw counterparts. The log specification reduces the influence of outliers and allows for an elasticity-based interpretation of the estimated coefficients. Observations with zero values are set to zero in the transformed variable.

We include ETF fixed effects (α_i) and day fixed effects (λ_t) to improve identification. The ETF fixed effects absorb time-invariant characteristics such as asset class, replication strategy, and baseline liquidity, while day fixed effects control for market-wide shocks, macroeconomic news, and common volatility. This specification ensures that identification is based on within-ETF variation over time and cross-sectional differences across ETFs on the same day. As a result, the design mitigates omitted variable bias and reduces noise from persistent ETF traits or broad market conditions.

We also estimate dynamic versions of the model that include lagged and lead terms of $logRFQ_{it}$ and $logCR_{it}$ to assess persistence and the temporal ordering of flows.

6.2 Results

Table 7 presents panel regression results relating RFQ activity to ETF primary market flows. Across all specifications, we find a robust positive association between $logCR$ and $logRFQ$. In columns (1)–(3), the coefficient on $logRFQ$ is consistently around 0.09 and statistically significant at the 1% level. This implies that a 1% increase in RFQ volume is associated with a 0.09–0.10% increase in ETF creations and redemptions on the same day. The positive and significant coefficient on $logRFQ\_lag1$ indicates that the effect extends into the following day, suggesting that some primary market activity may follow with a lag after RFQ execution.

The dynamic specifications in columns (4)–(6) confirm this persistence. Lagged values of $logCR$ are positively associated with current flows, indicating autocorrelation in primary market activity. Additionally, the predictive content of lagged $logRFQ$ diminishes after two days, and future values of $logRFQ$ are not significantly related to current $logCR$, supporting a temporal ordering from RFQs to primary flows.

These results point to a strong operational association between RFQs and ETF primary market activity. RFQs appear to trigger inventory adjustments by APs, as RFQ volume is positively associated with subsequent creations and redemptions, even after controlling for mispricing, volatility, liquidity, and ETF fixed effects. The magnitude and persistence of the relation suggest that RFQs are not simply correlated with market activity, but are instrumental in driving primary market flows. RFQs thus play a central role in the functioning of the ETF primary market, serving as the execution mechanism through which institutional trading demand prompts APs to initiate creations and redemptions.

6.3 Robustness

As a first robustness test, we examine whether the direction of RFQs aligns with the direction of ETF primary market activity. Building on our previous findings, we hypothesize that an RFQ purchase (sale) initiated by an institutional investor prompts an ETF creation (redemption) by APs. This mechanism reflects the institutional structure of ETF markets, where RFQs generate inventory pressures that APs address through primary market transactions. To determine the daily direction of RFQ activity, we infer the sign from Tradeweb intraday RFQs, aggregate these signs at the daily level, and apply the resulting daily sign to the total daily RFQ volume for each ETF. We then construct signed log measures for both

RFQ activity and ETF primary market flows by taking the logarithm of the absolute value of each flow plus one and multiplying by the corresponding sign. Days with zero total RFQ volume or zero primary market activity are assigned a value of zero before applying the log transformation. This procedure ensures that the direction and magnitude of RFQ flows are directly comparable to ETF creation and redemption flows. Table IA8 reports the estimates, which support our hypothesis. The positive and significant coefficient on $Signed\ logRFQ$ indicates that ETF creations are associated with RFQ purchase flows, while ETF redemptions are associated with RFQ sales.

Next, we test the robustness of our findings by inverting the baseline specification. While our main analysis regresses ETF primary market activity on RFQ flows, reversing the regression direction allows us to assess whether RFQ activity itself responds systematically to ETF primary market flows. In the dynamic specifications presented in Table IA9, the only significant coefficients are on $logCR$ and $logCR\_lead1$, while $logCR\_lag1$ and $logCR\_lag2$ are statistically insignificant. This asymmetry in timing supports the interpretation that ETF primary market activity tends to be contemporaneous with or follow RFQ trades, rather than precede them. Furthermore, RFQ activity remains positively associated with ETF primary market flows but shows little relation to ETF mispricing. Absolute mispricing ($abs(Mis)$) is statistically significant only in the first specification and is not robust across models. This evidence reinforces the view that RFQs are unlikely to reflect arbitrage activity and are instead primarily driven by liquidity demand rather than information.

These robustness checks support the main findings in Table 7: RFQs appear to trigger inventory adjustments by APs, and the timing of effects—from RFQ execution to subsequent ETF creations and redemptions—points to a directional mechanism associating institutional trading demand to primary market activity.

7 RFQs and Lit Market Quality

7.1 Empirical approach

Next, we examine how RFQ activity relates to lit market conditions at the daily frequency. We regress the log of total RFQ volume for each ETF-day, denoted $logRFQ_{it}$, on the log of lit market volume ($logLit$), daily volatility ($Volat$), quoted bid-ask spread ($BASpread$), and order book depth ($Depth$). Each of these variables enters the regression in its lagged, contemporaneous, and lead values to capture both feedback effects and the temporal ordering of activity. Specifically, we estimate:

$$
\begin{aligned}
\log RFQ_{it} = {} & \beta_1 \cdot \log Lit_{it-1} + \beta_2 \cdot \log Lit_{it} + \beta_3 \cdot \log Lit_{it+1} \\
& + \beta_4 \cdot Volat_{it-1} + \beta_5 \cdot Volat_{it} + \beta_6 \cdot Volat_{it+1} \\
& + \beta_7 \cdot BASpread_{it-1} + \beta_8 \cdot BASpread_{it} + \beta_9 \cdot BASpread_{it+1} \\
& + \beta_{10} \cdot Depth_{it-1} + \beta_{11} \cdot Depth_{it} + \beta_{12} \cdot Depth_{it+1} \\
& + \beta_{13} \cdot InvPrice_{it-1} + \beta_{14} \cdot MktCap_{it-1} + \alpha_i + \lambda_t + \varepsilon_{it} \qquad (4)
\end{aligned}
$$

where i indexes ETFs and t indexes trading days. All continuous variables are log-transformed to reduce the influence of outliers and to allow for an elasticity-based interpretation of the coefficients. Observations with zero values are set to zero in the transformed variables.

ETF fixed effects (α_i) control for time-invariant ETF characteristics such as asset class, replication strategy, and baseline liquidity. Day fixed effects (λ_t) absorb common shocks to market conditions, including macroeconomic events and broad shifts in risk appetite. This specification ensures that identification comes from within-ETF variation over time and cross-sectional differences across ETFs on the same day, thereby mitigating bias from unobserved heterogeneity and reducing noise from persistent ETF characteristics or common market shocks.

7.2 Results

Table 8 reports results for three subsamples based on daily RFQ volume: small (below €1 million), medium (€1–3 million), and large (above €3 million). In the large-RFQ sample, we find a strong and statistically significant association between RFQ volume and contemporaneous lit volume ($\beta = 0.10$, $p < 0.01$), suggesting that RFQ activity intensifies when lit market activity is also elevated. Additionally, RFQ volume is positively associated with lead lit volume and negatively associated with lead bid-ask spreads, indicating that large RFQs are typically executed during periods of high lit market volume and do not coincide with subsequent deterioration in lit market quality.

By contrast, associations in the medium- and small-RFQ samples are generally weaker or insignificant. The medium-RFQ group shows a modest but statistically significant relation with contemporaneous lit volume ($\beta = 0.01$, $p < 0.05$), while other coefficients are not meaningfully different from zero. In the small-RFQ sample, most estimates are imprecise, though some sensitivity to lagged volatility and depth suggests that small-scale RFQs may be more reactive to transitory fluctuations in market conditions.

Taken together, the results indicate that RFQ activity is most closely aligned with lit market conditions on high-RFQ days, consistent with a complementary—rather than substitutive—relation between trading mechanisms. The evidence supports the view that institutional investors use RFQs strategically during periods of elevated lit market activity, rather than displacing or undermining lit market liquidity. While our analysis is not causal and we do not observe the counterfactual in which RFQ trading is absent, the evidence does not support the concern that RFQs reduce lit venue activity—in fact, lit volume tends to be higher, not lower, on days with large RFQ usage.

Importantly, we find no evidence that RFQ activity deteriorates lit market quality. Measures of volatility, quoted spreads, and depth do not worsen following high-RFQ days. On the contrary, in the large-RFQ sample, RFQ volume is associated with improved liquidity in the following day, reinforcing the interpretation that RFQs operate alongside, rather than at the expense of, lit markets.

8 Conclusion

This paper investigates the role of RFQ trading in European ETF markets, where RFQs account for the majority of trading volume. Using granular trade-level data, we compare RFQs with lit market executions through a spread decomposition of trading costs and examine their interaction with ETF primary market activity and lit market conditions.

Our findings show that RFQs are consistently associated with significantly lower price impact than lit trades, even for comparable transactions. Regarding their effective spread, results vary depending on the ETF and trade size, but appear globally competitive with lit trades. This cost structure is consistent with the strategic use of RFQs to minimize information leakage and execution risk when handling institutional-size orders. Moreover, we document a strong and persistent positive association between RFQ activity and ETF primary market flows, consistent with RFQs being the primary execution mechanism through which institutional demand prompts authorized participants to initiate creations and redemptions.

Contrary to concerns that RFQs may undermine price discovery or drain liquidity from lit venues, we find no evidence that RFQ activity deteriorates lit market quality. On the contrary, RFQ usage tends to increase when lit market volume rises and is not associated with any persistent deterioration in lit market quality. These results point to a largely complementary relation between RFQ and lit trading mechanisms and underscore the importance of market structure in shaping execution outcomes.

While our findings point to a complementary relation between RFQs and lit venues within the current European fragmented market structure, we remain cautious in extrapolating these results to alternative institutional settings. In particular, we do not observe a counterfactual environment in which all ETF liquidity is consolidated on lit venues, nor can we assess how execution costs or market quality would evolve in the absence of RFQs. Our analysis is therefore best interpreted as characterizing the role and effectiveness of RFQs within the existing European ETF trading ecosystem, rather than as evidence in favor of any particular market design.

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Table 1: Variable Definitions and Data Sources
This table provides definitions for the main variables used in the analysis. The first column presents the variable names used throughout the paper. The second column describes each variable in detail. The Source column indicates the data origin.

Name	**Description**	**Source**
	Trade-Level Variables	
$\mathbb{1}_{RFQ}$	Indicator variable equal to one if the trade is an RFQ	BMLL
EffSpread	Effective spread of executed trades over a 60-second window (bps).	BMLL
RSpread	Realized spread measured over a 60-second window (bps).	BMLL
PImpact	Trade price impact measured over a 60-second window (bps).	BMLL
TradeSize	€trade size, log-transformed	BMLL
$\mathbb{1}_{Buy}$	Indicator variable equal to one if the trade is a buy	BMLL
TTI30A	Signed 30-minute €trade imbalance, log-transformed	BMLL
	Daily Variables	
logRFQ	Total notional of RFQ trades (€), log-transformed	BMLL
logCR	Total notional of primary market activity (absolute value of creation and redemption, €), log-transformed.	Bloomberg
logLit	Total notional of lit trades (€), log-transformed	BMLL
Mis	ETF mispricing (standardized at the ETF level).	Bloomberg
Ret	Daily ETF return (percentage terms).	Bloomberg
AbsRet	Absolute daily ETF return (percentage terms).	Bloomberg
Volat	Average intraday time-weighted volatility of 30-minute returns (percentage terms), log-transformed.	BMLL
BASpread	Average intraday time-weighted quoted bid-ask spread (bps), log-transformed.	BMLL
Depth	Average intraday time-weighted market depth at the 5th level on both bid and ask sides (€), log-transformed.	BMLL
	Intradaily Variables (30 minutes)	
Volat	Intraday ETF volatility (percentage terms).	BMLL
Spread	Average intraday bid-ask spread (bps).	BMLL
Depth	Sum of notional liquidity at the 5th level on both ask and bid sides (M EUR).	BMLL

Table 2: Spread Decomposition by Trade Size - Summary Statistics
Observations are at the ETF-trade frequency. $\mathbb{1}_{RFQ}$ is an indicator variable equal to one if the trade is an RFQ. SD denotes the standard deviation. Due to data availability only RFQs on Tradeweb are included. The variables are in basis points. Trades that exceed 3 million euros are included in the "Large" sample. Trades between 1 and 3 million euros are in the "Medium" sample. Trades below 1 million euros are classified as the "Small" sample. The sample consists of 90 ETFs observed from September 2021 to January 2025.

			EffSpread		*RSpread*		*PImpact*	
$\mathbb{1}_{RFQ}$	SizeBin	N	Mean	SD	Mean	SD	Mean	SD
0	Small	14,001,572	6.2	6.9	2.5	20.8	3.8	20.4
0	Medium	8,797	4.4	7.2	0.7	14.5	3.4	14.1
0	Large	586	4.7	7.3	1.7	14.3	3.0	12.0
1	Small	460,683	4.7	5.9	4.4	9.9	0.4	8.0
1	Medium	14,818	4.7	6.9	4.5	12.2	0.5	8.2
1	Large	10,416	7.8	10.2	8.3	17.5	0.8	8.2

Table 3: Spread Decomposition by Execution Mechanism

This table reports regression results for *EffSpread*, *RSpread*, and *PImpact* on $\mathbb{1}_{RFQ}$. Observations are at the ETF-trade frequency. We distinguish between trades executed via RFQ and those on the ETF's main lit venue. $\mathbb{1}_{RFQ}$ is an indicator equal to one if the trade is executed via RFQ rather than on the ETF's main lit order book. $\mathbb{1}_{Buy}$ is an indicator variable equal to one if the trade is a buy. Spreads are measured in basis points, and *TradeSize* is the logarithm of trade value (in €). All regressions include ETF, day, and 30-minute time-bin fixed effects. Standard errors are two-way clustered by ETF and day. Due to data availability, only RFQs on Tradeweb are included. The sample covers 90 ETFs observed from September 2021 to January 2025.

	EffSpread	*RSpread*	*PImpact*
$\mathbb{1}_{RFQ}$	-0.59^{***}	1.59^{***}	-2.02^{***}
	(0.21)	(0.22)	(0.18)
TradeSize	0.02	-0.11^{***}	0.14^{***}
	(0.01)	(0.03)	(0.02)
$\mathbb{1}_{Buy}$	0.94^{***}	2.27^{***}	-1.28^{***}
	(0.14)	(0.28)	(0.19)
Day FE	Y	Y	Y
ETF FE	Y	Y	Y
Time-Bin FE	Y	Y	Y
Sample	Full	Full	Full
Observations	14,496,872	14,496,872	14,496,872
R^2	0.30	0.02	0.05

Table 4: Spread Decomposition by Trade Size and Trade Imbalance
This table reports regression results for *EffSpread*, *RSpread*, and *PImpact* on an interaction between $\mathbb{1}_{RFQ}$ and recent trade imbalance. Observations are at the ETF-trade frequency. $\mathbb{1}_{RFQ}$ is an indicator equal to one if the trade is executed via RFQ rather than on the ETF's main lit order book. $\mathbb{1}_{Buy}$ is an indicator variable equal to one if the trade is a buy. *TTI30A* denotes the signed logarithm of the 30-minute trade imbalance; a positive value indicates recent trades were in the same direction as the current trade, and negative values suggest offsetting pressure. Due to data availability, only RFQs on Tradeweb are included. The sample consists of 90 ETFs observed from September 2021 to January 2025.

	EffSpread	*RSpread*	*PImpact*
$\mathbb{1}_{RFQ}$	-0.60^{***}	1.46^{***}	-1.90^{***}
	(0.21)	(0.22)	(0.18)
log(*TI30A*)	-0.003^{*}	-0.05^{***}	0.05^{***}
	(0.002)	(0.01)	(0.01)
$\mathbb{1}_{RFQ} \times \log(TI30A)$	0.01^{***}	0.04^{***}	-0.04^{***}
	(0.002)	(0.01)	(0.01)
TradeSize	0.02	-0.09^{***}	0.12^{***}
	(0.01)	(0.03)	(0.02)
$\mathbb{1}_{Buy}$	0.93^{***}	2.04^{***}	-1.06^{***}
	(0.13)	(0.23)	(0.18)
Day FE	Y	Y	Y
ETF FE	Y	Y	Y
Time-Bin FE	Y	Y	Y
Sample	Full	Full	Full
Observations	14,496,872	14,496,872	14,496,872
R^2	0.30	0.02	0.05

Table 5: Spread Decomposition by Execution Mechanism — Entropy-Balanced Sample
This table reports regression estimates of *EffSpread*, *RSpread*, and $PImpact$ on an indicator for RFQ execution. Observations are at the ETF-trade level. $\mathbb{1}_{RFQ}$ equals one if the trade is executed via RFQ rather than the ETF's main lit venue. Control-group observations are reweighted using entropy balancing on *TradeSize* to ensure that the weighted covariate distribution matches that of RFQ trades. Regressions are estimated with these entropy-balancing weights and include fixed effects for trading day, ETF, and 30-minute time bins. Spreads are measured in basis points; *TradeSize* is the log of trade value (in €). The entropy-balanced sample includes trades from 90 ETFs between September 2021 and January 2025.

	EffSpread	*RSpread*	$PImpact$
$\mathbb{1}_{RFQ}$	-0.31	1.81^{***}	-1.93^{***}
	(0.19)	(0.26)	(0.21)
TradeSize	-0.02	-0.12^{***}	0.11^{***}
	(0.02)	(0.04)	(0.02)
$\mathbb{1}_{Buy}$	1.08^{***}	2.20^{***}	-1.04^{***}
	(0.15)	(0.24)	(0.17)
Day FE	Y	Y	Y
ETF FE	Y	Y	Y
Time-Bin FE	Y	Y	Y
Sample	Balanced	Balanced	Balanced
Observations	6,318,627	6,318,627	6,318,627
R^2	0.26	0.05	0.03

Table 6: Spread Decomposition by Execution Mechanism — Matched Sample

This table reports regression estimates of *EffSpread*, *RSpread*, and *PImpact* on an indicator for RFQ execution. Observations are at the ETF-trade level. $\mathbb{1}_{\mathrm{RFQ}}$ equals one if the trade is executed via RFQ rather than the ETF's main lit venue. Trades are matched using nearest-neighbor Mahalanobis matching on *TradeSize*, with exact matching on ETF, trading day, and trade direction ($\mathbb{1}_{Buy}$). Regressions include fixed effects for trading day, ETF, and 30-minute time bins. Spreads are measured in basis points; *TradeSize* is the log of trade value (in €). The matched sample includes trades from 90 ETFs between September 2021 and January 2025.

	EffSpread	*RSpread*	*PImpact*
$\mathbb{1}_{RFQ}$	-0.68^{***}	1.40^{***}	-1.91^{***}
	(0.20)	(0.24)	(0.22)
TradeSize	-0.13^{***}	-0.23^{***}	0.10^{***}
	(0.04)	(0.06)	(0.02)
$\mathbb{1}_{Buy}$	0.75^{***}	1.24^{***}	-0.43^{***}
	(0.14)	(0.17)	(0.08)
Day FE	Y	Y	Y
ETF FE	Y	Y	Y
Time-Bin FE	Y	Y	Y
Sample	Matched	Matched	Matched
Observations	846,278	846,278	846,278
R^2	0.26	0.07	0.02

Table 7: ETF Primary Market Activity and Daily RFQs

RFQs and ETF primary market activity are computed as the log of their daily euro amounts. Zero values are replaced by 0 prior to log transformation. RFQs from both Tradeweb and Bloomberg are included. The sample consists of 90 ETFs observed from September 2021 to January 2025.

	logCR					
logRFQ	0.09***	0.09***	0.09***	0.10***	0.08***	0.10***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
logRFQ_lag1	0.09***		0.09***	0.08***		0.08***
	(0.02)		(0.02)	(0.02)		(0.02)
logRFQ_lag2	−0.02		−0.02	−0.02**		−0.02**
	(0.01)		(0.01)	(0.01)		(0.01)
logRFQ_lead1	−0.01		−0.01	−0.01		−0.01
	(0.01)		(0.01)	(0.01)		(0.01)
logRFQ_lead2	−0.04***		−0.04***	−0.04***		−0.04***
	(0.01)		(0.01)	(0.01)		(0.01)
logLit	0.79***	0.77***	0.77***	0.67***	0.66***	0.66***
	(0.08)	(0.08)	(0.08)	(0.07)	(0.07)	(0.07)
abs(Mis)	0.18**	0.18**	0.19**	0.16**	0.15**	0.15**
	(0.08)	(0.08)	(0.08)	(0.07)	(0.07)	(0.07)
Volat		0.10	0.11		0.15	0.16
		(0.14)	(0.14)		(0.12)	(0.12)
BASpread		−0.28	−0.29		−0.18	−0.19
		(0.22)	(0.22)		(0.18)	(0.17)
Depth		0.02	0.02		0.02	0.03
		(0.16)	(0.16)		(0.13)	(0.12)
logCR_lag1				0.06***	0.06***	0.06***
				(0.01)	(0.01)	(0.01)
logCR_lag2				0.05***	0.04***	0.05***
				(0.005)	(0.01)	(0.005)
logCR_lead1				0.05***	0.05***	0.05***
				(0.01)	(0.01)	(0.01)
logCR_lead2				0.05***	0.04***	0.04***
				(0.01)	(0.01)	(0.01)
ETF Fixed effects	Y	Y	Y	Y	Y	Y
Day Fixed effects	Y	Y	Y	Y	Y	Y
Observations	70,476	70,748	70,437	65,145	65,107	65,107
R^2	0.35	0.35	0.35	0.36	0.36	0.36

Table 8: Daily RFQs and Lit Market Quality by Trade Size
Observations are at the ETF-day frequency. RFQs from both Tradeweb and Bloomberg are included, with zero values replaced by 0 prior to log transformation. Days where RFQs exceed 3 million euros are included in the "Large" sample (column 3). Days with RFQs totaling between 1 and 3 million euros are in the "Medium" sample (column 2). Days with RFQs below 1 million euros are classified as the "Small" sample (column 1). Control variables include lagged inverse price, lagged market capitalization, and daily returns. The sample consists of 90 ETFs observed from September 2021 to January 2025.

	logRFQ		
	Small	Medium	Large
logLit_lag1	0.03	0.003	0.01
	(0.05)	(0.003)	(0.01)
logLit	0.07	0.01**	0.10***
	(0.05)	(0.004)	(0.01)
logLit_lead1	−0.002	−0.002	0.02**
	(0.05)	(0.005)	(0.01)
Volat_lag1	0.32**	−0.01	0.02
	(0.14)	(0.01)	(0.03)
Volat	0.31**	0.02	0.01
	(0.12)	(0.01)	(0.03)
Volat_lead1	0.36**	0.01	0.01
	(0.16)	(0.01)	(0.03)
BASpread_lag1	0.01	0.03	0.002
	(0.20)	(0.02)	(0.04)
BASpread	−0.17	−0.01	0.16***
	(0.20)	(0.02)	(0.04)
BASpread_lead1	−0.18	−0.03	−0.10**
	(0.19)	(0.02)	(0.04)
Depth_lag1	0.36**	−0.02	−0.03
	(0.15)	(0.02)	(0.03)
Depth	0.01	0.001	−0.05
	(0.14)	(0.02)	(0.04)
Depth_lead1	0.35**	0.004	−0.01
	(0.15)	(0.02)	(0.03)
ETF Fixed effects	Y	Y	Y
Day Fixed effects	Y	Y	Y
Observations	31,603	10,769	30,658
R^2	0.71	0.11	0.42

Figure 1: Spread Decomposition by Trade Size
This figure reports the average values of *EffSpread* and $PImpact$ across trade size categories. Observations are at the ETF-trade frequency and aggregated by trade size. We distinguish between trades executed via RFQ and those on the ETF's main lit venue. Spreads are measured in basis points, and *TradeSize* is the logarithm of trade value (in €). N denotes the number of trades in each category. Due to data availability, only RFQs on Tradeweb are included. The sample covers 90 ETFs observed from September 2021 to January 2025.

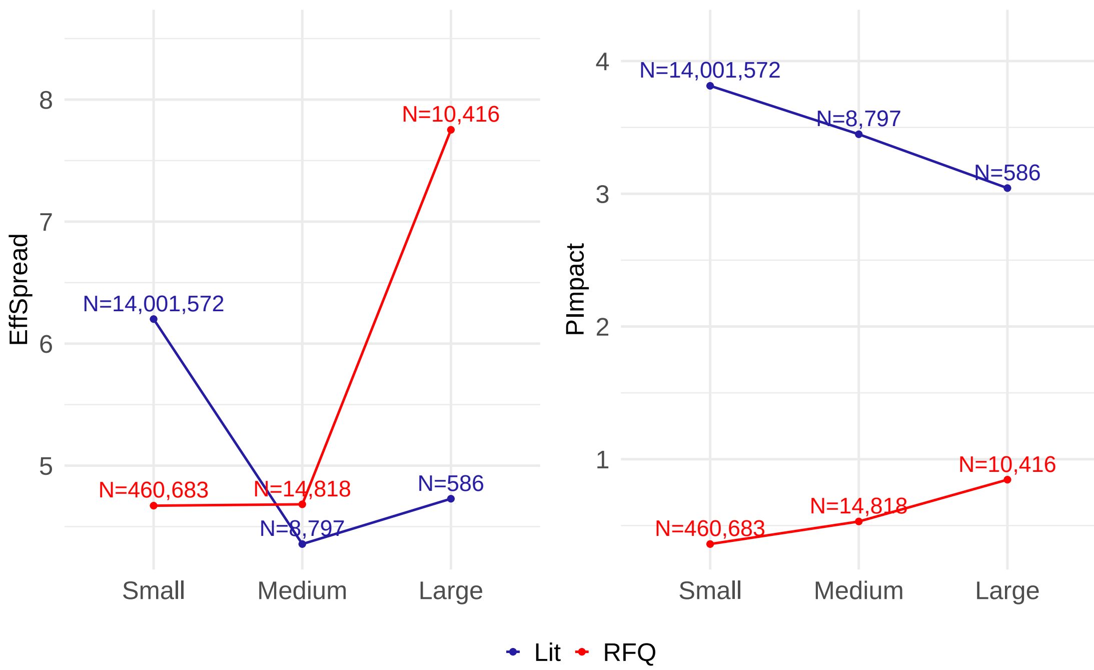


Figure 2: European ETF Trading volume per Trading Venue
BMTF designates Bloomberg, while TWEN designates Tradeweb; both venues are used for RFQs. The sample period extends from September 2021 to January 2025, and includes 90 ETFs, resulting in 3,349 ETF-venue-currency pairs. The sample includes 20 venues; here we present only the 8 largest to illustrate the volume concentration.

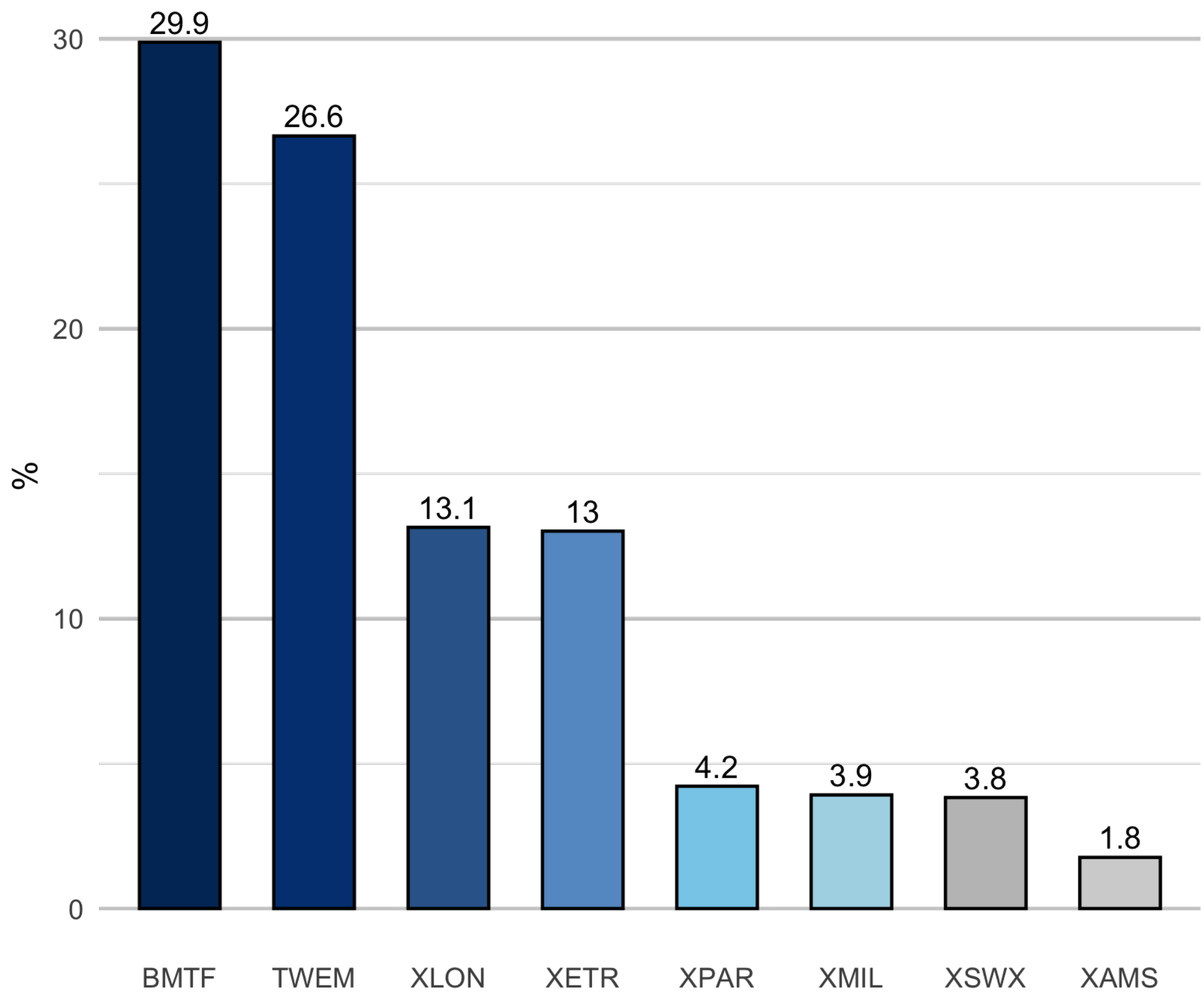
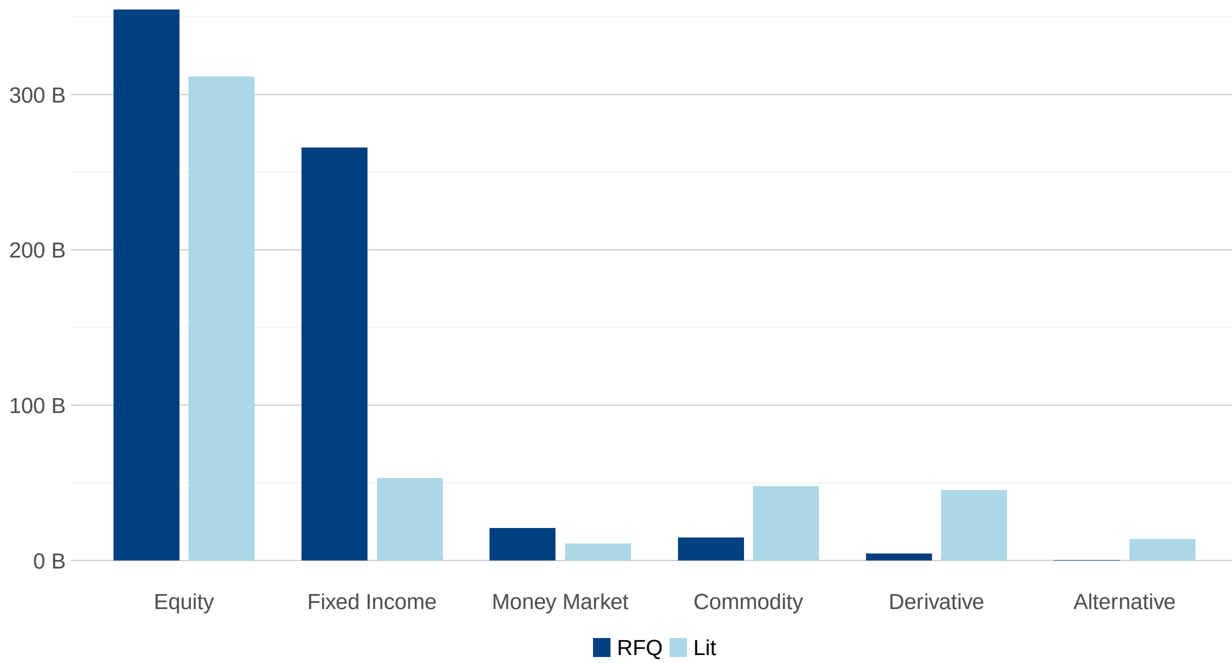


Figure 3: RFQ and Lit Volume by Asset Class
The sample includes 90 ETFs observed from September 2021 to January 2025. "Derivatives" refers to leveraged and inverse ETFs. We report total trading volume over the full sample period, in billions of euros.



Internet Appendix

Table IA1: Market Venues Sample
This table lists all European trading venues for which we have access through BMLL by their Market Identifier Codes (MICs). The sample period extends from September 2021 to January 2025, and includes 90 ETFs, 20 venues, resulting in 3,349 ETF-venue-currency pairs.

MIC	**Venue Name**
AQXE	Aquis Exchange Europe
AQEU	Aquis Exchange UK
BATE	CBOE Europe (BATS)
BMTF	Bloomberg MTF (we include both BMTF (UK), BTFE (EU))
BOTC	BOAT OTC Reporting
CEUX	CBOE Europe Equities (CXE)
CHIX	CBOE Europe (CHIX)
SGMX	SIGMA X (Frankfurt)
SGMU	SIGMA X (UK)
TQEX	Tradegate Exchange
TRQX	Turquoise Europe
TWEM	Tradeweb Europe MTF (we include both TREU (UK), TWEM (Amsterdam))
XAMS	Euronext Amsterdam
XETR	Deutsche Börse (Xetra)
XLON	London Stock Exchange
XMIL	Borsa Italiana
XPAR	Euronext Paris
XSTO	Nasdaq Stockholm
XSWX	SIX Swiss Exchange
XEQT	Equiduct

Table IA2: Spread Decomposition by Execution Mechanism at 20-Minute Horizon
This table reports regression results for *EffSpread*, *RSpread_20*, *PImpact_20*, and *PImpact_PT* on $\mathbb{1}_{RFQ}$, where realized spread and price impact are computed over a 20-minute window. *PImpact_PT* measures the 20-minute price impact using the midpoint observed 3 minutes before execution to account for potential market movements between the start of the RFQ process and execution. Observations are at the ETF-trade frequency. We distinguish between trades executed via RFQ and those on the ETF's main lit venue. $\mathbb{1}_{RFQ}$ is an indicator variable equal to one if the trade is an RFQ. Due to data availability, only RFQs on Tradeweb are included. The sample covers 90 ETFs observed from September 2021 to January 2025.

	EffSpread	*RSpread_20*	*PImpact_20*	*PImpact_PT*
$\mathbb{1}_{RFQ}$	-0.59^{***}	1.56^{***}	-1.92^{***}	-1.91^{**}
	(0.21)	(0.28)	(0.27)	(0.80)
TradeSize	0.02	-0.13^{***}	0.16^{***}	0.06^{***}
	(0.01)	(0.04)	(0.04)	(0.02)
Buy	0.94^{***}	0.47	0.49	-0.30
	(0.14)	(1.72)	(1.68)	(1.40)
Day FE	Y	Y	Y	Y
ETF FE	Y	Y	Y	Y
Time-Bin FE	Y	Y	Y	Y
Sample	Full	Full	Full	Full
Observations	13,860,747	13,860,747	13,860,747	14,073,652
R^2	0.30	0.003	0.01	0.01

Table IA3: Spread Decomposition by Execution Mechanism (Excluding Delayed RFQ Publications)

This table reports regression results for *EffSpread*, *RSpread*, and *PImpact* on $\mathbb{1}_{RFQ}$. Observations are at the ETF-trade frequency. We distinguish between trades executed via RFQ and those on the ETF's main lit venue. $\mathbb{1}_{RFQ}$ is an indicator equal to one if the trade is executed via RFQ rather than on the ETF's main lit order book. Spreads are measured in basis points, and *TradeSize* is the logarithm of trade value (in €). The sample excludes RFQ trades whose publication is delayed by more than one minute after execution. Due to data availability, only RFQs on Tradeweb are included. The sample covers 90 ETFs observed from September 2021 to January 2025.

	EffSpread	*RSpread*	*PImpact*
$\mathbb{1}_{RFQ}$	-0.66^{***}	1.50^{***}	-2.02^{***}
	(0.22)	(0.23)	(0.19)
TradeSize	0.02	-0.11^{***}	0.14^{***}
	(0.01)	(0.03)	(0.02)
$\mathbb{1}_{Buy}$	0.95^{***}	2.27^{***}	-1.28^{***}
	(0.14)	(0.28)	(0.19)
Day FE	Y	Y	Y
ETF FE	Y	Y	Y
Time-Bin FE	Y	Y	Y
Sample	Full	Full	Full
Observations	14,476,733	14,476,733	14,476,733
R^2	0.30	0.02	0.05

Table IA4: Spread Decomposition by Trade Size for Equity ETFs and Fixed Income ETFs
This table reports regression results for *EffSpread*, *RSpread*, and *PImpact* across trade size categories. Observations are at the ETF-trade frequency. We distinguish between trades executed via RFQ and those on the ETF's main lit venue. $\mathbb{1}_{RFQ}$ is an indicator variable equal to one if the trade is an RFQ. Spreads are measured in basis points, and *TradeSize* is the logarithm of trade value (in €). Panel A focuses on the top tercile of ETFs by lit volume. In the main specification presented in Panel B, we consider only equity ETFs, while in Panel C we present the estimates for Fixed Income ETFs. Due to data availability, only RFQs on Tradeweb are included. The sample covers 90 ETFs observed from September 2021 to January 2025.

Panel A: Top Tercile ETFs (lit volume)

	EffSpread	*RSpread*	*PImpact*
$\mathbb{1}_{RFQ}$	−0.45	1.23***	−1.61***
	(0.28)	(0.29)	(0.18)
TradeSize	0.02	−0.12***	0.14***
	(0.01)	(0.03)	(0.03)
$\mathbb{1}_{Buy}$	0.78***	2.25***	−1.51***
	(0.18)	(0.37)	(0.25)
Day FE	Y	Y	Y
ETF FE	Y	Y	Y
Time-Bin FE	Y	Y	Y
Sample	Liquid	Liquid	Liquid
Observations	10,638,054	10,638,054	10,638,054
R^2	0.31	0.02	0.06

Panel B: Equity ETFs

	EffSpread	*RSpread*	*PImpact*
$\mathbb{1}_{RFQ}$	−0.73**	1.35***	−1.99***
	(0.28)	(0.26)	(0.24)
TradeSize	−0.01	−0.13***	0.13***
	(0.02)	(0.04)	(0.03)
$\mathbb{1}_{Buy}$	1.12***	2.79***	−1.67***
	(0.18)	(0.34)	(0.20)
Day FE	Y	Y	Y
ETF FE	Y	Y	Y
Time-Bin FE	Y	Y	Y
Sample	Equity	Equity	Equity
Observations	8,513,614	8,513,614	8,513,614
R^2	0.26	0.05	0.03

Panel C: Fixed Income ETFs

	EffSpread	*RSpread*	*PImpact*
$\mathbb{1}_{RFQ}$	0.07	2.89***	−2.45***
	(0.30)	(0.61)	(0.43)
TradeSize	−0.05	−0.27*	0.22**
	(0.05)	(0.13)	(0.09)
$\mathbb{1}_{Buy}$	2.10***	2.80***	−0.22
	(0.27)	(0.43)	(0.39)
Day FE	Y	Y	Y
ETF FE	Y	Y	Y
Time-Bin FE	Y	Y	Y
Sample	Fixed Income	Fixed Income	Fixed Income
Observations	1,129,110	1,129,110	1,129,110
R^2	0.24	0.09	0.05

Table IA5: Spread Decomposition by Execution Mechanism – 5 Most Traded ETFs

This table reports regression results for *EffSpread*, *RSpread*, and *PImpact* on $\mathbb{1}_{RFQ}$. Observations are at the ETF-trade frequency. We distinguish between trades executed via RFQ and those on the ETF's main lit venue. $\mathbb{1}_{RFQ}$ is an indicator variable equal to one if the trade is an RFQ. Due to data availability, only RFQs on Tradeweb are included. The sample covers the 5 most traded ETFs observed from September 2021 to January 2025.

	EffSpread	*RSpread*	*PImpact*
$\mathbb{1}_{RFQ}$	-3.96^{***}	1.28^{***}	-5.52^{***}
	(0.16)	(0.11)	(0.24)
TradeSize	-0.14^{***}	0.04^{***}	-0.20^{***}
	(0.01)	(0.01)	(0.02)
$\mathbb{1}_{Buy}$	-0.12	2.45^{***}	-2.70^{***}
	(0.07)	(0.27)	(0.29)
Day FE	Y	Y	Y
ETF FE	N	N	N
Time-Bin FE	Y	Y	Y
Sample	Top 5	Top 5	Top 5
Observations	4,457,688	4,457,688	4,457,688
R^2	0.11	0.01	0.03

Table IA6: Spread Decomposition by Trade Size

This table reports regression results for *EffSpread*, *RSpread*, and *PImpact* on $\mathbb{1}_{RFQ}$ across trade size categories. Observations are at the ETF-trade frequency. We distinguish between trades executed via RFQ and those on the ETF's main lit venue. $\mathbb{1}_{RFQ}$ equals one if the trade is an RFQ. Trades exceeding 3 million euros are classified as "Large," trades between 1 and 3 million euros as "Medium," and trades below 1 million euros as "Small." Due to data availability, only RFQs on Tradeweb are included. The sample covers 90 ETFs observed from September 2021 to January 2025.

	EffSpread			*RSpread*			*PImpact*		
	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
$\mathbb{1}_{RFQ}$	-0.679^{***}	1.208^{***}	2.723^{***}	1.458^{***}	5.499^{***}	7.854^{***}	-2.011^{***}	-3.521^{***}	-4.024^{***}
	(0.203)	(0.367)	(0.780)	(0.222)	(0.565)	(1.268)	(0.184)	(0.404)	(1.076)
TradeSize	0.014	0.366^{***}	0.173^{**}	-0.115^{***}	0.581^{***}	0.335^{**}	0.138^{***}	-0.178^{***}	-0.205^{**}
	(0.013)	(0.066)	(0.078)	(0.026)	(0.098)	(0.147)	(0.022)	(0.042)	(0.081)
$\mathbb{1}_{Buy}$	0.946^{***}	-0.085	-0.651^{***}	2.271^{***}	-0.202	-1.170^{***}	-1.284^{***}	0.273	0.267
	(0.135)	(0.230)	(0.237)	(0.276)	(0.262)	(0.376)	(0.195)	(0.179)	(0.202)
Sample	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
Day FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
ETF FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time-Bin FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
RFQ Trades	460,683	14,818	10,416	460,683	14,818	10,416	460,683	14,818	10,416
Observations	14,462,255	23,615	11,002	14,462,255	23,615	11,002	14,462,255	23,615	11,002
R^2	0.297	0.228	0.336	0.022	0.124	0.246	0.053	0.078	0.103

Table IA7: Absolute Value of the Spread Decomposition

This table reports regression results for $|EffSpread|$, $|RSpread|$, and $|PImpact|$ on $\mathbb{1}_{RFQ}$ and controls. Observations are at the ETF-trade frequency. We distinguish between trades executed via RFQ and those on the ETF's main lit venue. $\mathbb{1}_{RFQ}$ is an indicator variable equal to one if the trade is an RFQ. Due to data availability, only RFQs on Tradeweb are included. The sample covers 90 ETFs observed from September 2021 to January 2025.

	$\lvert EffSpread \rvert$	$\lvert RSpread \rvert$	$\lvert PImpact \rvert$
$\mathbb{1}_{RFQ}$	-0.78^{***}	-0.53^{**}	-1.22^{***}
	(0.25)	(0.22)	(0.17)
$TradeSize$	0.02	0.03^{*}	0.11^{***}
	(0.01)	(0.02)	(0.02)
$\mathbb{1}_{Buy}$	0.69^{***}	0.13^{*}	-0.79^{***}
	(0.10)	(0.07)	(0.11)
Day FE	Y	Y	Y
ETF FE	Y	Y	Y
Time-Bin FE	Y	Y	Y
Sample	Full	Full	Full
Observations	14,496,872	14,496,872	14,496,872
R^2	0.31	0.43	0.43

Table IA8: Signed ETF Primary Market Activity and Signed RFQs

Signed RFQ and ETF primary market flows are computed by taking the signed logarithm of their absolute amounts plus one. Zero values are replaced by 0 prior to log transformation. The sign of daily RFQ flows is based on Tradeweb RFQs. The sample includes 90 ETFs observed from September 2021 to January 2025.

	Signed logCR					
Signed logRFQ	0.02***	0.03***	0.02***	0.02***	0.02***	0.02***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Signed logRFQ_lag1	0.03***		0.03***	0.02***		0.02***
	(0.004)		(0.004)	(0.003)		(0.003)
Signed logRFQ_lag2	0.01**		0.01**	0.001		0.001
	(0.004)		(0.004)	(0.004)		(0.004)
Signed logRFQ_lead1	0.01**		0.01**	0.004		0.004
	(0.004)		(0.004)	(0.004)		(0.004)
Signed logRFQ_lead2	0.004		0.004	0.001		0.001
	(0.003)		(0.003)	(0.003)		(0.003)
logLit	0.45***	0.45***	0.44***	0.29***	0.28***	0.28***
	(0.09)	(0.10)	(0.10)	(0.06)	(0.07)	(0.07)
abs(Ret)	−0.20**	−0.22**	−0.22**	−0.14*	−0.16**	−0.15*
	(0.10)	(0.09)	(0.09)	(0.08)	(0.08)	(0.08)
abs(Mis)	0.18*	0.15	0.17*	0.13*	0.13	0.13*
	(0.11)	(0.10)	(0.10)	(0.08)	(0.08)	(0.08)
Volat		0.24	0.24		0.23	0.22
		(0.29)	(0.29)		(0.18)	(0.18)
BASpread		−0.03	−0.05		−0.15	−0.15
		(0.36)	(0.36)		(0.22)	(0.22)
Depth		−0.14	−0.13		−0.01	−0.01
		(0.24)	(0.24)		(0.13)	(0.13)
Signed logCR_lag1				0.10***	0.10***	0.10***
				(0.01)	(0.01)	(0.01)
Signed logCR_lag2				0.08***	0.08***	0.08***
				(0.01)	(0.01)	(0.01)
Signed logCR_lead1				0.10***	0.10***	0.10***
				(0.01)	(0.01)	(0.01)
Signed logCR_lead2				0.08***	0.09***	0.08***
				(0.01)	(0.01)	(0.01)
Day Fixed effects	Y	Y	Y	Y	Y	Y
ETF Fixed effects	Y	Y	Y	Y	Y	Y
Observations	71,662	71,956	71,623	71,662	71,623	71,623
R^2	0.07	0.06	0.07	0.12	0.12	0.12

Table IA9: Daily RFQs and ETF Primary Market Activity
RFQs and ETF primary market activity are computed as the log of their daily euro amounts. Zero values are replaced by 0 prior to log transformation. RFQs from both Tradeweb and Bloomberg are included. The sample consists of 90 ETFs observed from September 2021 to January 2025.

	logRFQ					
logCR	0.02***	0.02***	0.02***	0.01***	0.01***	0.01***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
logCR_lag1	0.002		0.002	−0.002		−0.002
	(0.003)		(0.003)	(0.002)		(0.002)
logCR_lag2	−0.003		−0.003	−0.01***		−0.01***
	(0.003)		(0.003)	(0.002)		(0.002)
logCR_lead1	0.01***		0.01***	0.01***		0.01***
	(0.003)		(0.003)	(0.003)		(0.003)
logCR_lead2	0.002		0.002	−0.004**		−0.004**
	(0.002)		(0.002)	(0.002)		(0.002)
logLit	0.24***	0.22***	0.21***	0.15***	0.15***	0.15***
	(0.05)	(0.05)	(0.05)	(0.02)	(0.02)	(0.02)
abs(Ret)	0.21***	0.19***	0.18***	0.12***	0.12***	0.11***
	(0.05)	(0.04)	(0.04)	(0.02)	(0.02)	(0.02)
abs(Mis)	0.12**	0.09*	0.10*	0.02	0.01	0.01
	(0.05)	(0.05)	(0.05)	(0.02)	(0.02)	(0.02)
Volat		0.52***	0.52***		0.08**	0.08**
		(0.13)	(0.13)		(0.04)	(0.04)
BASpread		−0.13	−0.09		0.05	0.06
		(0.24)	(0.24)		(0.06)	(0.06)
Depth		0.33**	0.34**		0.04	0.04
		(0.17)	(0.17)		(0.04)	(0.04)
logRFQ_lag1				0.15***	0.15***	0.15***
				(0.01)	(0.01)	(0.01)
logRFQ_lag2				0.13***	0.12***	0.13***
				(0.01)	(0.01)	(0.01)
logRFQ_lead1				0.15***	0.16***	0.15***
				(0.01)	(0.01)	(0.01)
logRFQ_lead2				0.14***	0.13***	0.14***
				(0.01)	(0.01)	(0.01)
Day Fixed effects	Y	Y	Y	Y	Y	Y
Stock Fixed effects	Y	Y	Y	Y	Y	Y
Observations	65,145	70,748	65,107	65,145	70,437	65,107
R^2	0.81	0.81	0.81	0.87	0.86	0.87