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

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Abstract

We study the role of Request-for-Quote (RFQ) trading in European ETF markets, where RFQs account for most trading volume. Using granular trade-level data, we compare RFQs to lit market executions through a spread decomposition framework. RFQs involve higher effective spreads but consistently exhibit lower price impact. While lit trades have greater price impact that also increases with trade imbalance, RFQs decouple execution costs from prevailing order flow. We document a strong association between RFQ activity and ETF primary market flows, consistent with RFQs triggering creations and redemptions. RFQs offer institutional investors a mechanism to manage costs and limit 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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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)). Block trading mechanisms—whether upstairs markets or dark venues—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 sharp segmentation of trading activity: small trades concentrate on lit venues, while RFQs dominate as the preferred channel for executing large institutional orders.

Next, to formally assess the relationship between execution mechanism and trading costs, we estimate panel regressions of effective spread, realized spread, and price impact, comparing RFQ trades to lit market trades while controlling for trade size and other relevant factors. By including ETF and time fixed effects, our approach helps account for differences in asset characteristics and market conditions, reducing potential biases from venue selection or time-varying liquidity. Our results show that although RFQ trades generally have higher effective and realized spreads—especially for small transactions—they consistently exhibit lower price impact. This difference is economically meaningful: small trades on lit venues benefit from tighter quoted spreads but face substantial price impact due to market response and information leakage. In contrast, RFQs facilitate large, single-point executions at higher spreads but with minimal market reaction, thereby avoiding cumulative price pressure and reducing exposure to directional flow.

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. We find that price impact increases with imbalance for lit trades but not for RFQs, suggesting RFQs decouple price impact from prevailing order flow and alleviate cumulative market impact. This indicates RFQs are strategically used to lower execution costs and uncertainty for large institutional trades. To account for this endogenous venue choice, we apply the two-stage procedure from Hendershott and Madhavan (2015) to correct for potential selection bias in our price impact estimates. After adjusting for self-selection, our key findings hold: RFQ trades still show higher effective spreads but notably lower price impact than lit trades. More broadly, these results are robust to varying measurement windows and consistent across ETF types, liquidity levels, and trade sizes, reinforcing that RFQs reduce price impact.

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 block 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 showing that RFQs facilitate large trades with limited price impact despite higher effective spreads than lit trades, reflecting their value in providing immediate liquidity while reducing information leakage. RFQs are largely uninformed, exhibiting modest price impact that does not rise with trade imbalance, unlike lit executions. We also document a strong link between RFQ activity and ETF primary market flows, indicating RFQs as the primary channel for institutional demand driving creations and redemptions. Lastly, RFQ usage is concentrated in specific environments but does not degrade lit market quality; volatility, spreads, and depth remain stable, and lit trade volumes increase on high-RFQ days. These results advance the block trading and dark execution literature by demonstrating that RFQs support large, uninformed trades without impairing lit liquidity or market quality.

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. Section 5 investigates the link between RFQs and ETF creation/redemption flows. Section 6 assesses whether RFQs substitute for or complement lit market activity. Section 7 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, 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) highlight 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.

Block trading mechanisms, such as upstairs markets and more recently dark venues, have emerged as alternatives that mitigate these frictions. Madhavan (1995) and Keim and Madhavan (1997) show that block trades can achieve lower market impact and better execution quality than smaller trades exposed to 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 studying RFQs as a distinct block execution mechanism within the European ETF market. RFQs share features with both dark and block trading venues, offering large-size execution without pre-trade transparency. 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 emphasize 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 block 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 are 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

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

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 considered 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 trading costs through a standard spread decomposition, which separates the effective spread into a realized component and a residual capturing price impact. For each trade, we compute:

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

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 sells, $+1$ for buys). 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 observed. For RFQ trades,

[2]We also test a Δ of 20 minutes in the robustness section with results presented in Table IA3.

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.

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-size block trading. For example, over the sample period, we record more than 16 million small lit trades (notional under €1 million) but only 532,590 small RFQs. Conversely, there are 12,481 large RFQ trades (notional above €3 million) compared to only 353 large lit trades. This imbalance underscores the specialization of trading mechanisms according to trade size and execution objectives.

Second, trades executed via RFQ tend to have a higher effective spread than those on lit venues, particularly for medium-sized trades (€1–3 million). Specifically, the average *EffSpread* for RFQ trades in this bin is 5.8 basis points, compared to 1.7 basis points for lit-venue trades. Despite this higher upfront cost, RFQ trades consistently exhibit lower price impact, averaging around 1 basis point across trade sizes.

These patterns are illustrated in Figure 1, which reports the average effective spread, realized spread, and price impact across trade size bins and execution mechanisms, highlighting both the segmentation of execution mechanisms and the contrast in transaction cost components.

The difference in *PImpact* between RFQ and lit-venue execution is particularly notable. For small trades, RFQ executions result in an average *PImpact* of only 1.6 basis points, compared to 4.9 basis points for lit-venue trades. A gap also holds for large trades (2.8 vs. 6.5 basis points), although it is important to note that large lit trades are infrequent. Specifically, the sample contains only 353 large lit trades, compared to 12,481 large RFQ trades.

This scarcity of large lit trades complicates identification in this part of the distribution. Nonetheless, the inference remains economically meaningful. Small lit trades—of which there are more than 16 million—exhibit an average price impact of 4.9 basis points. This suggests that splitting a large order across multiple small lit trades would accumulate substantial market impact, rapidly exceeding the effective spread of the counterfactual full order executed via RFQ. In this sense, even absent direct lit-market comparisons at large sizes, the summary statistics suggest a rationale for RFQ use.

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:

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

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). We include ETF fixed effects (α_i) to control for time-invariant differences across ETFs, and day fixed effects (λ_t) to absorb common shocks and market-wide variation in liquidity conditions. Standard errors are clustered at the ETF and day levels.

To control for predictable intraday dynamics, we also include fixed effects for 30-minute time windows. Specifically, we partition the trading day into half-hour intervals and assign each trade to a corresponding time bin based on its timestamp.

3.5 Results

Table 3 presents coefficient estimates from regressions of *EffSpread*, *RSpread*, and *PImpact* on an RFQ indicator, controlling for trade size and fixed effects. Higher *EffSpread* and *RSpread* are associated with RFQ execution, with statistically significant coefficients of 1.08

and 2.45 basis points, respectively ($p < 0.01$), indicating transaction costs. In line with Madhavan (1995), lower *PImpact* is associated with RFQ execution: the coefficient on $\mathbb{1}_{\mathrm{RFQ}}$ is -1.27 and statistically significant at the 1% level, suggesting that RFQ execution substantially mitigates market impact relative to lit-venue trading.

Since RFQs are frequently used for large trades, the evidence is consistent with institutions accepting higher effective spreads in exchange for immediate execution and reduced information leakage. Executing large orders through a series of smaller lit-venue trades would likely result in higher cumulative price impact, making the total execution cost of such a strategy exceed that of an RFQ. The higher effective spreads observed for RFQs thus indicate a deliberate trade-off for minimizing price pressure. RFQ use, therefore, emerges as a cost-efficient execution strategy in fragmented and transparent markets.

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. In the absence of the interaction, the coefficient on *TI30A* captures the sensitivity of lit-market trades to recent directional flow. Consistent with prior work on order flow toxicity, higher trade imbalance is associated with significantly higher price impact for lit executions: the coefficient on *TI30A* in the *PImpact* regression is 0.05 ($p < 0.05$), indicating that lit trades become more costly in the presence of persistent flow in the same direction.

By contrast, the interaction term $\mathbb{1}_{RFQ} \times TI30A$ is negative and statistically significant ($\beta = -0.04$, $p < 0.10$), suggesting that RFQ trades are less sensitive to recent trade imbalances. This muted response implies that RFQs are insulated from the path-dependent execution costs observed on lit venues. For *EffSpread*, the interaction is statistically insignificant, while for *RSpread*, the coefficient is positive and significant, consistent with dealers widening quotes in response to directional flow but absorbing the associated market risk.

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 Endogenous Selection of Execution Mechanism

4.1.1 Empirical Approach

A key concern when comparing execution outcomes across RFQ and lit venues is the potential endogeneity of execution choice. Larger or more complex trades are more likely to be routed through RFQ, while smaller or simpler trades tend to execute on the lit order book. To address this, we implement a two-stage selection correction procedure in the spirit of Madhavan and Cheng (1997) and Hendershott and Madhavan (2015), who examine endogenous venue choice in market microstructure settings. In the first stage, we estimate a probit model in which the dependent variable is $\mathbb{1}_{RFQ}$, and the regressors include trade size, trade direction (buy or sell), and time-of-day controls. From the fitted model, we compute the Inverse Mills Ratio (IMR) to capture the conditional probability of selecting RFQ execution. In the second stage, we regress *EffSpread*, *RSpread*, and *PImpact* on the set of covariates of the first stage, augmented with the IMR to control for potential selection bias.

4.1.2 Results

The second-stage regression estimates presented in Table 5 confirm our main findings. After correcting for execution mechanism selection, RFQ trades are associated with effective spreads that are 0.84 basis points higher and price impacts that are 1.89 basis points lower than lit trades, both significant at the 1% level. The coefficient on the inverse Mills ratio is generally weakly significant to insignificant, suggesting that selection into RFQ execution based on unobserved characteristics does not materially bias the estimates.

4.2 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. 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. Summary statistics for this alternative specification are reported in Table IA2, and the corresponding regression results are presented in Table IA3. The results remain

[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.

qualitatively unchanged, confirming that our main findings are robust to the choice of Δ.

4.3 Robustness across asset class and liquidity

To further evaluate the robustness of the baseline results, we re-estimate the main specification across three subsamples: the top tercile of ETFs by trading volume, equity ETFs, and fixed income ETFs. These subsample analyses address potential heterogeneity in market microstructure across asset classes and liquidity tiers. Differences in the liquidity of the underlying securities between equity and fixed income ETFs may influence both the execution choice and its associated cost. Figure 3 plots total trading volume in lit and RFQ markets by asset class, highlighting the dominance of RFQ execution in both categories. For fixed income ETFs, RFQs account for 83% of total trading volume, suggesting that execution behavior in this segment may be shaped by lower baseline liquidity and a higher prevalence of block trades. In parallel, we consider the top tercile of ETFs by trading volume to test whether more actively traded ETFs—those benefiting from greater market depth and faster information incorporation—exhibit different execution dynamics. These robustness tests allow us to assess whether the observed spread-impact trade-off varies systematically with market liquidity or asset class.

First, the most actively traded ETFs (Panel A of Table IA4) present results similar to the full sample. Higher *EffSpread* is associated with RFQ execution (coefficient of 1.37 basis points), while lower *PImpact* is associated with RFQ execution (coefficient of -0.60, significant at the 5% level). Even in these highly liquid ETFs, RFQs help reduce price impact. To account for concentration in trading activity, we also confirm that price impact is lower for RFQs within the five most actively traded ETFs (see Table IA5). In this specification, ETF fixed effects are excluded to avoid multicollinearity risk in the restricted sample. In contrast to the main specification, RFQs in this subsample are also associated with significantly lower *EffSpread*.

In the equity ETF subsample (Panel B of Table IA4), higher *EffSpread* is associated with RFQ execution, but the coefficient of 0.33 basis points is not statistically significant. However, lower *PImpact* is associated with RFQ execution, with a coefficient of -1.60, significant at the 1% level. This evidence suggests that RFQs entail comparable effective spreads but shield trades from adverse market reactions. The result supports the interpretation that RFQs are used strategically to avoid the cumulative price pressure and information leakage associated with order splitting on lit venues.

The fixed income ETF subsample (Panel C) exhibits an even more pronounced spread-impact trade-off. Higher *EffSpread* is associated with RFQ execution, with a coefficient of 1.99 basis points, while lower *PImpact* is associated with RFQ execution, with a coefficient of -1.61, both significant at the 1% level. These effects are consistent with the lower baseline liquidity in fixed income markets, where slicing orders would lead to greater slippage and signaling costs. The results indicate that RFQs allow market participants to execute large trades while minimizing execution costs and market disruption.

Overall, the evidence across all subsamples consistently supports the interpretation that RFQs are employed to reduce execution costs by facilitating block trades while limiting market impact.

4.4 Robustness Across Trade Size

To assess whether the effects of RFQ execution vary across the size distribution, we estimate the regression specification separately for small, medium, and large trades. Table IA6 reports the coefficient estimates for each cost component.

RFQ trades are systematically associated with lower price impact across small and medium trade sizes. The coefficient on $\mathbb{1}_{RFQ}$ in the *PImpact* regression is -1.363 basis points for small trades and -0.993 for medium trades, both significant at the 1% level. For large trades, the coefficient on $\mathbb{1}_{RFQ}$ in the *PImpact* regression is -0.470 and not statistically significant. This is consistent with the extremely limited number of large lit-venue executions in the sample. Of the 12,834 large trades, 12,481 are RFQs, implying only 353 large trades executed on lit venues. Given the inclusion of day, 30-minute, and ETF fixed effects, the effective identifying variation in this segment is minimal. As a result, statistical power is limited, and the imprecise estimate should not be interpreted as evidence against the impact-reducing role of RFQs. Overall, the results confirm that RFQ execution mitigates market impact, particularly in small and medium trades where lit execution is more prevalent and sequential order splitting would generate observable price pressure.

In contrast to the consistent negative relation observed for *PImpact*, higher *EffSpread* and *RSpread* are associated with RFQ execution, particularly for medium and large trades. The coefficient on $\mathbb{1}_{\text{RFQ}}$ in the *EffSpread* regression increases from 0.749 basis points for small trades to 3.916 and 7.579 basis points for medium and large trades, respectively. *RSpread* shows a similar progression. These estimates suggest that RFQs tend to execute at wider quoted spreads.

Overall, the results highlight a clear spread-impact trade-off: while RFQs entail higher quoted spreads, they reduce price impact. The cost advantage of RFQs is particularly evident in the small and medium size segments, where the risk of cumulative market impact from lit execution is greatest. These findings support the interpretation that RFQs are used strategically to minimize total execution costs.

4.5 Robustness to Absolute Value of the Spread Decomposition

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, lower $|PImpact|$ is associated with RFQ execution, with a coefficient of -1.57, significant at the 1% level.

Unlike the main specification, lower $|EffSpread|$ is also associated with RFQ execution in this specification. This suggests that the higher *EffSpread* observed for RFQs in the main results could be partly driven by trade direction misclassification.

5 ETF Primary Market Activity and RFQs

5.1 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.

5.2 Results

Table 6 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.

5.3 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 6: 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.

6 RFQs and Lit Market Quality

6.1 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.

6.2 Results

Table 7 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.

7 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 from both Tradeweb and Bloomberg, we compare RFQs to lit market executions through a decomposition of trading costs and analyze their interaction with ETF primary market activity and lit market conditions.

Our findings show that while RFQs tend to exhibit higher effective spreads than lit trades, they are consistently associated with significantly lower price impact even for medium and large transactions. This cost structure is consistent with the strategic use of RFQs to minimize information leakage and execution risk for 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
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	16,161,025	7.0	12.3	2.4	74.9	4.9	76.4
0	Medium	8,356	1.7	10.2	-0.5	38.0	2.0	36.5
0	Large	353	0.3	11.3	-6.1	46.8	6.5	37.8
1	Small	532,590	5.9	8.4	4.8	33.4	1.6	33.0
1	Medium	17,230	6.1	10.3	4.9	35.8	2.1	33.2
1	Large	12,481	9.8	15.2	9.2	42.0	2.8	33.3

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. Spreads are measured in basis points, and *TradeSize* is the logarithm of trade value (in €). Due to data availability, only RFQs on Tradeweb are included. The sample covers 90 ETFs observed from September 2021 to January 2025.

	EffSpread	*RSpread*	$PImpact$
$\mathbb{1}_{RFQ}$	1.08^{***}	2.45^{***}	-1.27^{***}
	(0.30)	(0.27)	(0.25)
TradeSize	-0.33^{***}	-0.39^{***}	0.06
	(0.08)	(0.05)	(0.09)
ETF Fixed Effects	Y	Y	Y
Day Fixed Effects	Y	Y	Y
30-min Fixed Effects	Y	Y	Y
Sample	Full	Full	Full
Observations	16,731,215	16,721,304	16,720,785
R^2	0.18	0.02	0.08

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. *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*
TI30A	0.01^{*}	-0.04^{***}	0.05^{**}
	(0.01)	(0.01)	(0.02)
$\mathbb{1}_{RFQ} \times TI30A$	-0.01	0.03^{**}	-0.04^{*}
	(0.01)	(0.01)	(0.02)
$\mathbb{1}_{RFQ}$	1.11^{***}	2.33^{***}	-1.12^{***}
	(0.31)	(0.27)	(0.29)
TradeSize	-0.33^{***}	-0.38^{***}	0.04
	(0.08)	(0.05)	(0.09)
ETF Fixed Effects	Y	Y	Y
Day Fixed Effects	Y	Y	Y
30-min Fixed Effects	Y	Y	Y
Sample	Full	Full	Full
Observations	16,731,215	16,721,304	16,720,785
R^2	0.18	0.02	0.08

Table 5: Spread Decomposition by Execution Mechanism with Selection Correction
This table reports OLS regression results for *EffSpread*, *RSpread*, and *PImpact* on $\mathbb{1}_{RFQ}$. Observations are at the ETF-trade level. $\mathbb{1}_{RFQ}$ is an indicator equal to one if the trade is executed via RFQ rather than on the ETF's main lit order book. Regressors include *TradeSize* (log of trade value in €), trade direction ($\mathbb{1}_{Buy}$), and asset class dummies. To address potential endogeneity in execution choice, we include the Inverse Mills Ratio (*IMR*), estimated from a first-stage probit model of $\mathbb{1}_{RFQ}$ on the same set of regressors. Spreads and impact are measured in basis points. Only RFQs from Tradeweb are included. The sample covers 90 ETFs from September 2021 to January 2025.

	EffSpread	*RSpread*	*PImpact*
$\mathbb{1}_{RFQ}$	0.84***	2.83***	−1.89***
	(0.31)	(0.33)	(0.25)
TradeSize	11.20*	−4.01	15.59*
	(6.03)	(3.16)	(8.43)
$\mathbb{1}_{Buy}$	3.49**	1.02	2.52
	(1.70)	(1.00)	(2.46)
AssetClassCommodity	60.53*	−22.13	85.04*
	(35.03)	(18.72)	(48.59)
AssetClassDerivative	28.47*	−11.88	42.06*
	(16.84)	(8.76)	(23.47)
AssetClassEquity	72.69*	−26.73	102.28*
	(41.60)	(22.12)	(57.85)
AssetClassFixedIncome	86.05*	−29.10	118.33*
	(48.20)	(25.59)	(67.08)
AssetClassMoneyMarket	49.33	−22.32	73.84*
	(31.46)	(16.83)	(43.61)
IMR	57.64*	−18.49	78.14*
	(30.34)	(15.87)	(42.49)
Constant	−71.31	134.96***	−203.38*
	(81.23)	(42.85)	(113.31)
Day Fixed Effects	N	N	N
ETF Fixed Effects	N	N	N
Sample	Full	Full	Full
Observations	16,731,215	16,721,304	16,720,785
R^2	0.09	0.01	0.04

Table 6: 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 7: 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.

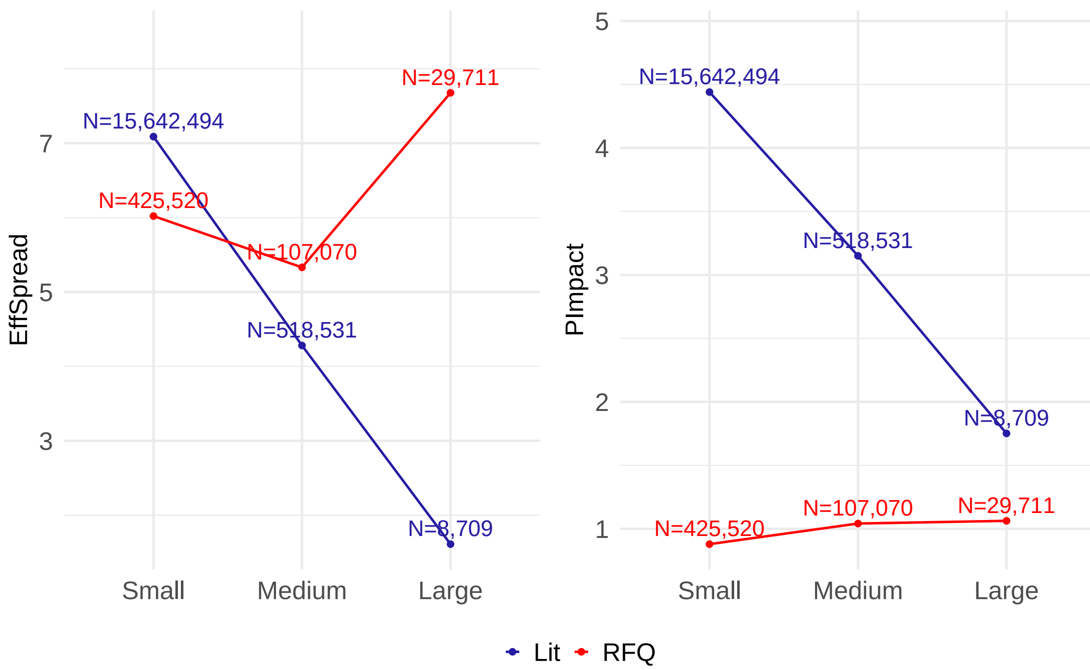


Figure 2: European ETF Trading volume per Trading Venue
BMTF designates Bloomberg, while TWEN designates Tradeweb; both venues are used for RFQs. The sample period extends from September 2021 to January 2025, and includes 90 ETFs, resulting in 3,349 ETF-venue-currency pairs. The sample includes 20 venues;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

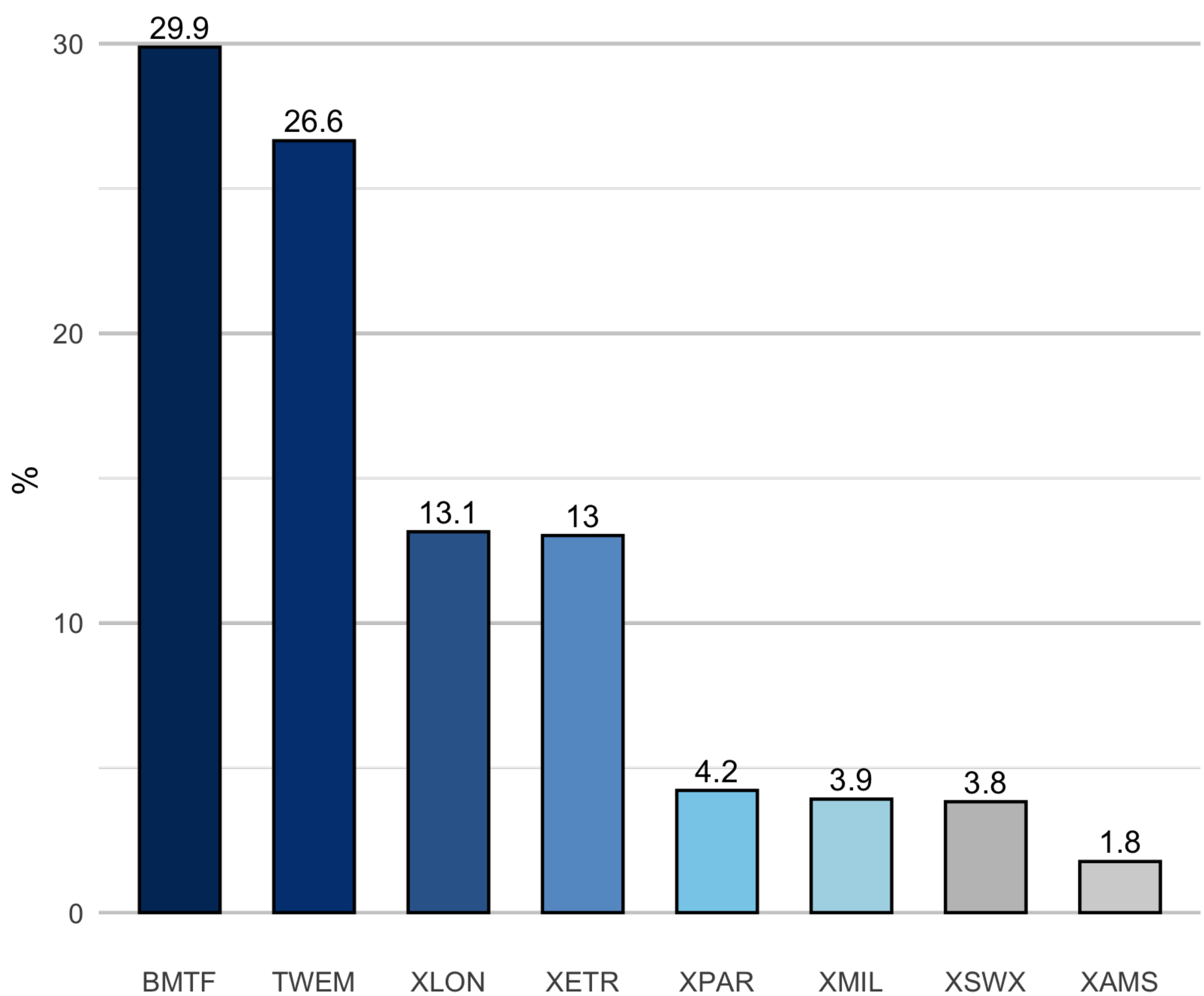
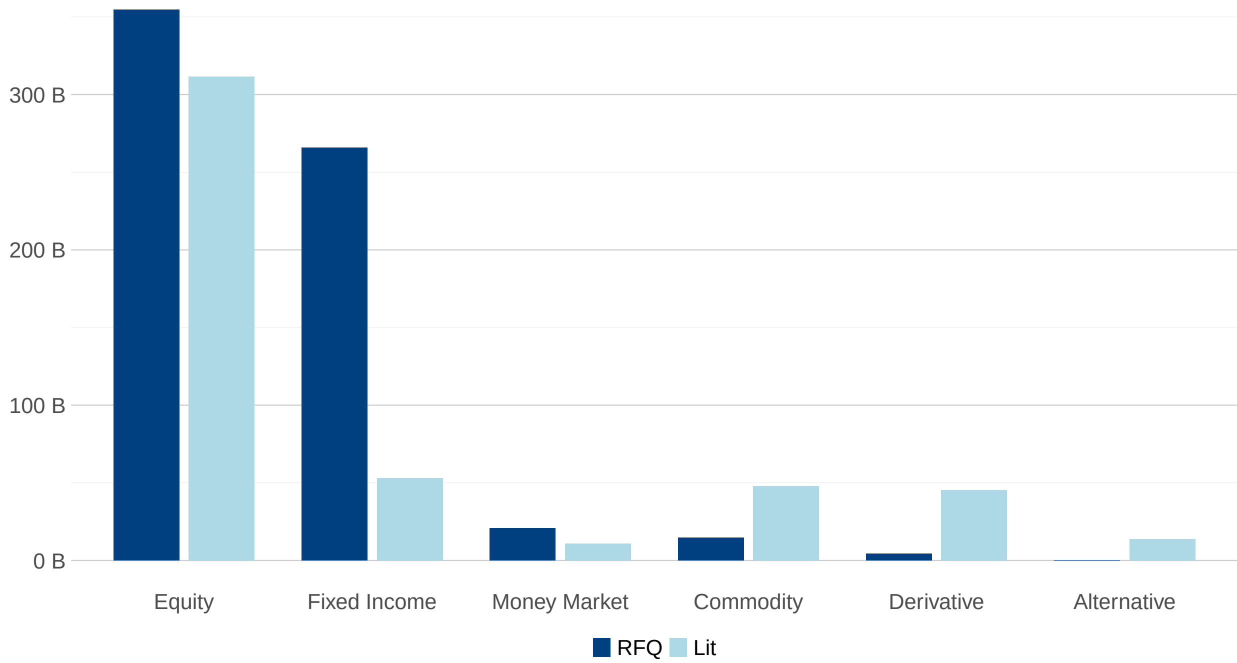


Figure 3: RFQ and Lit Volume by Asset Class
The sample includes 90 ETFs observed from September 2021 to January 2025. "Derivatives" refers to leveraged and inverse ETFs. We report total trading volume over the full sample period, in billions of euros.



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 Trade Size - Summary Statistics at 20-Minute Horizon
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_20*		*PImpact_20*	
$\mathbb{1}_{RFQ}$	SizeBin	N	Mean	SD	Mean	SD	Mean	SD
0	Small	16,161,025	7.0	12.3	2.4	74.9	4.9	76.4
0	Medium	8,356	1.7	10.2	-0.5	38.0	2.0	36.5
0	Large	353	0.3	11.3	-6.1	46.8	6.5	37.8
1	Small	532,590	5.9	8.4	4.8	33.4	1.6	33.0
1	Medium	17,230	6.1	10.3	4.9	35.8	2.1	33.2
1	Large	12,481	9.8	15.2	9.2	42.0	2.8	33.3

Table IA3: Spread Decomposition by Execution Mechanism at 20-Minute Horizon

This table reports regression results for *EffSpread*, *RSpread_20*, and *PImpact_20* on $\mathbb{1}_{RFQ}$, where realized spread and price impact are computed over a 20-minute window. 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*
$\mathbb{1}_{RFQ}$	1.08^{***}	2.46^{***}	-0.78^{***}
	(0.30)	(0.30)	(0.29)
TradeSize	-0.33^{***}	-0.43^{***}	0.08
	(0.08)	(0.05)	(0.07)
ETF Fixed Effects	Y	Y	Y
Day Fixed Effects	Y	Y	Y
30-min Fixed Effects	Y	Y	Y
Sample	Full	Full	Full
Observations	16,731,215	16,721,304	16,720,785
R^2	0.18	0.02	0.08

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*
$\mathbb{1}_{RFQ}$	1.37***	2.07***	−0.60**
	(0.39)	(0.35)	(0.28)
TradeSize	−0.33***	−0.36***	0.03
	(0.11)	(0.07)	(0.12)
Day Fixed Effects	Y	Y	Y
ETF Fixed Effects	Y	Y	Y
Sample	Full	Full	Full
Observations	12,067,123	12,058,117	12,057,671
R^2	0.19	0.01	0.08

Panel B: Equity ETFs

	EffSpread	*RSpread*	*PImpact*
$\mathbb{1}_{RFQ}$	0.33	2.00***	−1.60***
	(0.34)	(0.29)	(0.29)
TradeSize	−0.23***	−0.39***	0.16***
	(0.03)	(0.06)	(0.04)
Day Fixed Effects	Y	Y	Y
ETF Fixed Effects	Y	Y	Y
Sample	Full	Full	Full
Observations	9,632,327	9,632,562	9,632,315
R^2	0.13	0.03	0.02

Panel C: Fixed Income ETFs

	EffSpread	*RSpread*	*PImpact*
$\mathbb{1}_{RFQ}$	1.99^{***}	3.76^{***}	-1.61^{***}
	(0.50)	(0.54)	(0.22)
TradeSize	-0.33^{***}	-0.56^{***}	0.20^{***}
	(0.05)	(0.05)	(0.04)
Day Fixed Effects	Y	Y	Y
ETF Fixed Effects	Y	Y	Y
Sample	Full	Full	Full
Observations	1,530,057	1,530,054	1,530,033
R^2	0.14	0.09	0.02

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*
$\mathbb{1}_{RFQ}$	-3.04^{***}	1.77^{***}	-5.02^{***}
	(0.25)	(0.14)	(0.28)
TradeSize	-0.76^{***}	-0.14^{***}	-0.64^{***}
	(0.04)	(0.02)	(0.05)
ETF Fixed Effects	N	N	N
Day Fixed Effects	Y	Y	Y
30-min Fixed Effects	Y	Y	Y
Sample	Top 5	Top 5	Top 5
Observations	5,101,432	5,099,277	5,099,268
R^2	0.08	0.01	0.04

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. $\mathbb{1}_{RFQ}$ is an indicator variable equal to one if the trade is an RFQ. In this specification, 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
$\mathbb{1}_{RFQ}$	-0.778^{**}	-1.152^{***}	1.501	-0.401	-0.749^{*}	1.203	-1.561^{***}	-2.997^{***}	-2.597^{***}
	(0.321)	(0.359)	(1.020)	(0.271)	(0.407)	(1.076)	(0.250)	(0.359)	(0.705)
TradeSize	-0.109^{**}			-0.044^{*}			0.109^{*}		
	(0.052)	(0.000)	(0.000)	(0.026)	(0.000)	(0.000)	(0.059)	(0.000)	(0.000)
ETF Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Day Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
30-min Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
RFQ Trades	532,590	17,230	12,481	532,590	17,230	12,481	532,590	17,230	12,481
Observations	16,692,816	25,571	12,828	16,682,924	25,556	12,824	16,682,405	25,556	12,824
R^2	0.318	0.229	0.289	0.414	0.215	0.268	0.405	0.239	0.263

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.

	$\lvert EffSpread \rvert$	$\lvert RSpread \rvert$	$\lvert PImpact \rvert$
$\mathbb{1}_{RFQ}$	-0.64^{**}	-0.28	-1.57^{***}
	(0.32)	(0.27)	(0.25)
TradeSize	-0.11^{**}	-0.04	0.11^{*}
	(0.05)	(0.03)	(0.06)
ETF Fixed Effects	Y	Y	Y
Day Fixed Effects	Y	Y	Y
30-min Fixed Effects	Y	Y	Y
Sample	Full	Full	Full
Observations	16,731,215	16,721,304	16,720,785
R^2	0.18	0.02	0.08

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