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MARKET-MAKING VS. MATCHMAKING: AN EMPIRICAL ANALYSIS USING TRACE DATA

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Abstract: This study investigates the impact of Basel III Leverage Ratio and MiFID II on market-making and matchmaking dynamics in the U.S. corporate bond market. Utilizing transaction-level TRACE data, the analysis uncovers shifts in dealer strategies, liquidity provision and trade execution efficiency. Results reveal matchmaking's unexpected yield advantages and superior profitability, while market-making retains its critical liquidity premium. Employing weighted Difference-in-Differences (DiD) regressions, the study highlights the nuanced effects of regulation across trade groups and counterparties. By addressing search frictions and regulatory pressures, the findings offer valuable insights for shaping balanced frameworks in decentralized financial markets.

Keywords: search frictions, market-making, matchmaking, corporate bond market, MiFID II, Basel III Leverage Ratio, liquidity dynamics

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1 Introduction

The U.S. corporate bond market has undergone significant transformations in recent years, driven by post-crisis regulatory measures such as MiFID II and the Basel III Leverage Ratio. These regulations have fundamentally altered trading dynamics by imposing stricter capital requirements on financial institutions and promoting greater transparency. In this context, the traditional role of market-makers—characterized by their ability to provide immediate liquidity by holding inventory—has faced increasing constraints, prompting a shift toward matchmaking mechanisms, where dealers act as intermediaries without holding inventory. This shift raises critical questions about how trading mechanisms adapt to regulatory changes and how these adaptations impact key market outcomes, such as trade volumes, prices, yield and profits.

This study explores these dynamics using transaction-level data from the TRACE Bond Trade (BTDS) database, focusing on three distinct periods to capture pre-regulation conditions, the regulatory implementation phase and post-regulation adjustments. The analysis employs a weighted Difference-in-Differences (DiD) framework to investigate how market-making and matchmaking trades evolved under these constraints. By examining specific trade groups and counterparty types, the research provides a granular perspective on how different market participants adapted to the changing landscape.

This paper contributes to the existing literature by linking theoretical insights with empirical evidence to assess the nuanced impacts of regulation on trading mechanisms. While prior studies, such as Saar et al. (2023) and Adrian and Shin (2010), provide valuable theoretical frameworks, this study extends their work by incorporating a comprehensive dataset to analyze real-world trading behaviors. The findings underscore the complex interplay between regulatory interventions, dealer strategies and market outcomes, offering valuable implications for policymakers and market participants.

In the following sections, this paper first reviews the existing literature on search frictions, market-making and matchmaking in financial markets, with a particular focus on the regulatory context of Basel III Leverage Ratio and MiFID II. The methodology section then outlines the analytical approach, including the use of transaction-level TRACE data and a weighted Difference-in-Differences (DiD) framework, to examine trading behavior across the three observation periods. The empirical results are presented alongside their discussion, highlighting the evolution of market-making and matchmaking dynamics, with a focus on trade groups, counterparty types and regulatory impacts. The paper subsequently addresses the limitations of the analysis before concluding with a summary of key insights and potential directions for future research.

2 Literature Review

This chapter reviews the key theoretical frameworks and empirical studies that shape our understanding of search frictions and their implications for market structures, particularly in light of regulatory interventions and evolving trading mechanisms.

2.1 Theoretical Foundations of Search Frictions

The seminal work by Duffie et al. (2005) provides the foundational theoretical framework for understanding search frictions in financial markets. It models the trade-offs between immediacy and transaction costs, illustrating how delays in finding trading partners widen bid-ask spreads and reduce liquidity. Dealers play a key role in mitigating these frictions by acting as liquidity providers. Extensions by Vayanos and Wang (2012) incorporate risk aversion and market heterogeneity to analyze liquidity dynamics under varying market conditions. Weill (2007) further explores pricing inefficiencies caused by search frictions in OTC markets, showing how these frictions lead to deviations from fundamental asset values. These studies collectively highlight the importance of dealer behavior and market structure in determining the severity of search frictions.

2.2 Empirical Evidence on Search Frictions

Empirical research supports these theoretical insights. Bao et al. (2018) find that post-2008 regulatory constraints led to longer trade execution times and wider bid-ask spreads in corporate bond markets. Schultz (2017) similarly documents liquidity declines following regulatory changes, particularly for large or illiquid trades. Electronic trading platforms have partially mitigated these frictions by improving transparency and reducing counterparty search times. Goldstein et al. (2007) highlight how platforms like MarketAxess enhance market efficiency for smaller, liquid trades but remain limited in addressing large or complex transactions reliant on traditional dealer intermediation.

2.3 Market-Making and Matchmaking

Post-crisis regulatory changes have amplified the distinction between market-making and matchmaking. Market-making, where dealers hold inventory for immediate trade execution, has been constrained by higher capital requirements under Basel III (Anderson and Stulz, 2017). Saar et al. (2023) theoretically model this shift, showing how regulatory pressures push dealers toward matchmaking—acting as intermediaries without holding inventory. This transition reduces capital intensity but introduces time delays, complicating counterparty matching and potentially exacerbating search frictions.

Saar et al. (2023) analyze how regulatory constraints compel bank-affiliated dealers to reassess their role in liquidity provision. Their model identifies equilibrium states based on whether bank and nonbank dealers face constraints. When bank-affiliated dealers are heavily constrained, nonbank-affiliated dealers may partially offset the reduction in liquidity by increasing market-making activities. However, this rebalancing is limited, as nonbank-affiliated dealers often lack the balance sheet capacity and risk tolerance to fully replace the liquidity traditionally provided by banks. These theoretical findings align with empirical evidence showing that while matchmaking mechanisms have gained traction, they remain less effective for large and illiquid trades (Adrian and Shin, 2010). Saar et al. (2023) also highlight the dynamic nature of dealer strategies, suggesting that evolving market conditions or regulatory changes could further shift the balance between market-making and matchmaking.

2.4 Regulatory Impacts on Dealer Behavior

Regulatory interventions have fundamentally reshaped dealer incentives and behavior in OTC markets. Bao et al. (2018) observe that higher capital requirements have reduced bank-affiliated dealers' inventory holdings, diminishing their market-making activities and liquidity provision, particularly during periods of stress when dealer inventories are critical for absorbing shocks. Conversely, nonbank dealers, which are less constrained by regulation, have expanded their roles in liquidity provision but lack the capacity to fully offset the declines caused by reduced bank-affiliated dealer activity (Anderson and Stulz, 2017).

2.5 Technological Innovations and Search Frictions

The rise of electronic trading platforms and algorithmic trading has introduced new dynamics into the study of search frictions. Platforms like MarketAxess and Tradeweb enhance transparency and reduce search costs, particularly for smaller trades (Goldstein et al., 2007). Hendershott et al. (2011) show that algorithmic trading compresses spreads and boosts efficiency, though benefits vary by trade size and complexity. Foucault et al. (2016) explore the dual role of high-frequency trading, noting its potential to enhance liquidity while also increasing market fragmentation. These findings underscore the nuanced impact of technology on search frictions.

2.6 Gaps in the Literature and Directions for Future Research

Despite significant progress in understanding search frictions, several gaps remain. Much of the literature relies on proxies such as trade execution times and bid-ask spreads to measure search frictions, which may not fully capture the complexity of dealer-client interactions (Li and Schürhoff, 2019). Additionally, the heterogeneity of market participants and trading environments challenges the empirical validation of theoretical models. For instance, the assumption of homogeneous search costs and seamless transitions from market-making to matchmaking overlooks the nuanced realities of market structures.

This study seeks to address these gaps by leveraging TRACE transaction-level data to analyze the impact of regulatory changes on search frictions and trading mechanisms in the corporate bond market. By focusing on the heterogeneity of trade sizes and counterparty types, the research aims to provide a more comprehensive understanding of how market participants adapt to evolving regulatory and technological landscapes. In doing so, it bridges the gap between theory and practice, offering insights into the long-term implications of policy interventions on market efficiency and investor welfare.

3 Methodology

This chapter outlines the methodological approach used to analyze the transition between market-making and matchmaking in the U.S. corporate bond market. The analysis is based on transaction-level data from the enhanced TRACE Bond Trade (BTDS) database, accessed via WRDS and covers three distinct periods: December 1, 2016, to January 31, 2017 (pre-regulation control period), December 1, 2017, to January 31, 2018 (main observation period during regulatory implementation) and December 1, 2018, to January 31, 2019 (post-regulation control period).

To ensure a manageable dataset and maintain analytical depth, a random sample of three corporate bonds was drawn for the main observation period. These bonds were selected based on the criterion of having at least 10,000 trade observations to ensure sufficient size for robust statistical comparisons and to reduce the influence of outliers. This targeted approach allows for meaningful analysis while balancing time constraints and dataset manageability. Naturally, the same companies were analyzed in both control periods to ensure consistency and comparability across the observation windows.

These periods were deliberately chosen to capture the effects of MiFID II and the Basel III Leverage Ratio while ensuring consistent time gaps and avoiding potential distortions from external events like the COVID-19 pandemic. The methodological framework focuses on the impact of regulatory changes on trading mechanisms, trade groups and counterparty types, providing a nuanced understanding of market-making and matchmaking dynamics.

3.1 Regulatory Changes in January 2018

In January 2018, two significant regulatory changes were implemented that potentially impacted the U.S. corporate bond market: the Basel III Leverage Ratio and MiFID II.

The Basel III Leverage Ratio became effective on January 1, 2018. It is a non-risk- based capital requirement introduced by the Basel Committee on Banking Supervision, requiring banks to maintain a minimum Tier 1 capital of 3% of their total exposures, including off-balance-sheet items (Bank of International Settlements, 2014). This global regulatory standard aimed to constrain excessive leverage and enhance the resilience of the banking sector. For U.S. banks, the implementation of the leverage ratio potentially impacted their market-making activities in the corporate bond market by increasing the cost of holding inventories, thus affecting liquidity provision (Federal Reserve Board, 2014).

MiFID II (Markets in Financial Instruments Directive II) was introduced in the European Union and became effective on January 3, 2018. It aimed to enhance market transparency and investor protection. Although primarily affecting European markets, MiFID II had indirect effects on the U.S. corporate bond market. U.S. financial institutions with operations in Europe had to comply with the new regulations, leading to adjustments in their global trading practices. The increased transparency requirements and trading obligations could have influenced liquidity and trading volumes in the U.S. market as firms adapted their strategies (Johnson, 2018).

These regulatory changes were selected due to their potential impact on trading behaviors and liquidity in the U.S. corporate bond market. A comparison with the control periods enables the analysis of short-term effects, with two months selected for each period to balance analytical depth and dataset manageability. While this approach introduces challenges due to seasonal factors—such as December's end-year trading surge and January's new-year adjustments—it remains justified by the focus on immediate outcomes and the structured comparison to the control periods.

3.2 Data Cleaning and Validation

The data cleaning process aimed to ensure accuracy and reliability by addressing discrepancies and inconsistencies in trade records. The detailed description of the cleaning steps presented here refers specifically to the main investigation period (2017/18). However, the same procedures were applied analogously to the other two periods to maintain consistency across datasets. The Trade Status variable (`trc_st`) categorized trades into five types: Trade Report (`T`), Trade Cancel (`X`), Cancelled Correction (`C`), New Correction (`R`) and Reversal (`Y`). The absolute frequencies of these categories were examined to identify any anomalies. For trades classified as (`R`) and (`Y`), the Reference Number (`msg_seq_nb`) was missing, which is necessary to identify the trade to which the correction or late report refers. To address this, the Prior Reference Number (`orig_msg_seq_nb`) was substituted for the Reference Number to find the corresponding trade. Initially, (`R`) and (`C`) trades were matched to their corresponding (`T`) trades. These instances involved a trade being corrected and then the correction being canceled. Consequently, all matched (`R`) and (`C`) trades were deleted to avoid double-counting. In the main investigation period (2017/18), there were three (`C`) trades that could only be matched with a single (`T`) trade. These were not double-canceled corrections or canceled corrections referring to a Trade Cancel (`X`) but simply ones that could only be matched with one (`T`) trade; thus, they were deleted as invalid transactions. In total, all 330 (`R`) and 333 (`C`) trades were removed for this period. In the other two datasets, all (`C`) and (`R`) trades could be matched and were likewise deleted accordingly. Subsequently, all (`T`) trades (four observations) that had corresponding (`Y`) reversals were deleted. For the remaining 14 (`Y`) trades lacking a Reference Number, the Bloomberg Identifier ID (`bloomberg_identifier`) was used to match and remove the associated (`T`) trades. These steps ensured that all reversals were accounted for and that no invalid transactions remained. Additionally, all 228 (`X`) trades and their corresponding 228 (`T`) trades were removed, as these did not represent valid transactions. Without these adjustments, the actual trading volume would have been overestimated, misrepresenting market activity (Dick-Nielsen, 2014). Primary market trades were excluded from the dataset due to their minimal number of observations compared to secondary market trades. Furthermore, variables such as Buyer Commission and Seller Commission were removed, as over 99% of cases did not provide commission information. Ideally, these commissions should be added to the trade price to reflect the full transaction cost, but given their near-complete absence, the prices considered here do not fully incorporate potential commission effects. These cleaning steps ensured that the dataset for the main investigation period and the two control periods was accurate and reliable.

3.3 Statistical Analysis

Before identifying outliers and classifying data, all trades with a volume above $100 million were dropped. This threshold was chosen because, during the main observation period, the largest trade involved 3 billion units, the second-largest 1.84 billion units and the third-largest only 70 million units. Maintaining these extreme observations would have significantly distorted even the outlier data, especially when compared to the two control periods, which have no such extreme outliers, making comparison between the periods difficult. The analysis began with a series of descriptive and exploratory procedures (histograms, Q-plots, boxplots, normality tests) to understand the distributions of key variables: volume (`entrd_vol_qt`), price (`rptd_pr`), percentage yield (`yld_pt`) and (`profit`). Profit was calculated using the formula:

$$\text{Profit} = \text{Volume} \times \text{Price} \times \left(\frac{\text{Percentage Yield}}{100}\right)$$

Pairwise correlations between profit and its components revealed that volume exhibited the greatest variation and had the strongest influence on profit. Yield and especially price showed relatively smaller fluctuations and less impact on the overall variation in profit. Given these insights, the decision was made to focus outlier detection solely on the volume variable. By isolating trades with extremely large volumes, it is possible to examine whether the observed differences in prices and yields result from genuinely distinct market conditions or merely reflect the influence of very large trades. Outliers were addressed using three detection methods. The Median Absolute Deviation (MAD) calculates deviations from the median and is robust to skewed distributions, making it effective for the heavily skewed volume variable (Leys et al., 2013). The Interquartile Range (IQR) method identifies outliers outside 1.5 times the interquartile range (Tukey, 1977), but in this case, IQR identified fewer outliers than MAD. The Z-score method, commonly applied to normal distributions, was by far the least effective due to the dataset's non-normality (Cousineau and Chartier, 2010). Comparing these three methods improved the understanding of the data. Ultimately, the MAD method was chosen for outlier identification, as it was most suitable for the highly skewed volume distribution. After identifying volume-based outliers, the dataset could be split into two subsets: one containing trades with extremely large volumes (outliers) and one with relatively small volumes (non-outliers). This division enabled a more differentiated analysis, allowing a direct comparison of market conditions and outcomes across segments with different trade sizes. Following these procedures for each period, all three datasets were then combined. Since the earlier created variable (`year`) alone was insufficient to distinguish December and January trades within the same year, a (`month_year`) variable was introduced. Additionally, some key variables were converted into numeric formats to facilitate their inclusion in regressions. A variable named (`trade_group`) was created based on profit thresholds, dividing the dataset into micro trades

($\leq 100,000\$$), odd-lot trades ($> 100,000\$$ & $\leq 1,000,000\$$), round-lot trades ($> 1,000,000\$$ & $\leq 5,000,000\$$) and block trades ($> 5,000,000\$$) (Goldstein et al., 2007). These groups support analyses that focus on trade size segments, offering another layer of differentiation alongside the volume-based outlier classification.

3.4 Pair Matching and Market Mechanism Classifications

Trades were matched to classify them as market-making or matchmaking based on time differences. Matching relied on identical bond identifiers and profits, with opposing buy/sell indicators. Profit was selected as the distinguishing feature because it is derived from three highly precise variables: price (recorded to three decimal places), yield (to six decimal places) and volume (reported as integer values). This granularity makes it statistically improbable for unrelated trades to share identical profit values, ensuring accurate pair matching and minimizing the risk of misclassifying unrelated trades. In cases where there were unmatched trades or trades with excess buy/sell positions, the unmatched trades were removed. For example, if there were two buy trades and three sell trades, one sell trade was excluded to ensure that each part of the trade had only one matching counterpart. This process reduced the main dataset from 40,667 observations to 24,652 observations, ultimately resulting in 12,326 matched trades. Time differences between matched pairs were then calculated to classify trades. Although no widely accepted threshold for distinguishing market-making from matchmaking trades currently exists in the literature, a cutoff of 15 minutes was initially applied, guided by the fact that TRACE regulations require trades to be reported within this timeframe (FINRA, 2020). To further assess robustness and ensure that the classification did not rely solely on the regulatory reporting window, additional cutoffs of 1 and 5 minutes were tested. The decision to ultimately select a 1-minute cutoff was motivated by indirect evidence from the literature: While no studies explicitly define a time threshold or quantify the exact ratio of market-making to matchmaking, data from Bessembinder et al. (2018, 32, Table VI) show that the vast majority of trading volume in the corporate bond market involves principal trades by dealers. These principal trades can be interpreted as inventory-based, classic market-making activities where dealers use their own inventories to provide liquidity. According to Bessembinder et al. (2018), the share of such principal trades often exceeds 90%—particularly among bank-affiliated dealers—indicating that market-making heavily dominates trading activity. In this study, the 1-minute threshold (see Table 2) identified a similarly high proportion of seemingly inventory-based trades (market-making), making it a reasonable compromise for delineating the two trading mechanisms.

3.5 Regression Analysis

The selection of variables for the regression focused on their ability to explain differences between market-making and matchmaking. Since the variable (`profit`) was calculated from volume, price and yield, only the components of profit were included in the models to avoid multicollinearity. Similarly, the variable (`trade_group`) was excluded because its classification is based on the level of profit. As the selected companies stem from a random sample and do not represent the entire market, the inclusion of (`company_symbol`) was omitted to prevent distortions from firm-specific effects. The final choice for the dependent variable was the binary variable (`trade_type_numeric_3`), distinguishing between market-making (`0`) and matchmaking (`1`). The independent variables included volume, price, yield and two dummy variables for the counterparty ID (`cntra_mp_id_numeric`), classifying trades into non-member affiliate (`0`), customer (`1`) and interdealer (`2`) categories. Using interdealers as the reference category allows robust comparisons against the more prevalent reference group (Long and Freese, 2014).

Due to heteroskedasticity and non-normally distributed data, OLS regressions were excluded (White, 1980). A robust regression was attempted but failed because all weights were set to zero, leaving no observations. Instead, regressions with robust standard errors were employed to enhance flexibility and reliability. Furthermore, given the focus on the regulatory event's impact between December and January, a Difference-in-Differences (DiD) approach was selected. The DiD models offered slightly higher R^2 values than the regressions with robust standard errors and helped isolate the effect of the post-implementation period with the previously created (`post`) variable, with regression coefficients showing nearly identical tendencies across models. This consistency reinforced the suitability of the DiD framework for capturing the incremental regulatory effect.

Throughout the analysis, prices and yields were weighted by volume to ensure that large, economically significant trades received appropriate emphasis. Such volume weighting is well-established in financial studies as it ensures that data reflects market activity accurately (Jones et al., 1994). Applying similar weighting to the regression models ensured consistency with earlier descriptive findings and more accurately represented market behavior. A comparison between weighted and unweighted DiD regressions revealed that weighted DiD models produced consistently higher R^2 values, offering clearer insights and better alignment with the volume-weighted perspective. While logistic regressions were also considered—given that (`trade_type_numeric_3`) is a binary dependent variable and Logit models are well-suited for binary outcomes (Hosmer et al., 2013)—the weighted Logit approach yielded noticeably lower R^2 values compared to both unweighted Logit and DiD regressions, with a marked sensitivity to weighting adjustments.

In conclusion, the weighted DiD regressions align with the established weighting paradigm, offering improved explanatory power and producing stable, interpretable results consistent with the broader empirical findings. For transparency, the results of both the Logit regressions and the unweighted DiD regressions for all observation periods and datasets are presented in Tables 34–36 of the Appendix. While these alternative methods were considered, they exhibited lower explanatory power and greater sensitivity to weighting adjustments. These qualities confirm the weighted DiD approach as the primary regression method for the subsequent analyses, which are presented in detail in the next chapter.

4 Results and Discussion

This section presents the empirical findings from analyzing transaction-level data across the three periods, with a focus on the main observation period when MiFID II and the Basel III Leverage Ratio took effect. The results are structured as follows: First, general patterns and comparisons across periods are discussed. This is followed by analyses of market-making and matchmaking trades (Hypothesis 1), differences in dealer types and variations across trade groups. Finally, regression analyses are presented to compare models and provide a comprehensive understanding of the observed patterns.

4.1 General Patterns and Period Comparisons

The analysis in this section is based primarily on Tables 1 and 2 in the appendix.

The main observation period (2017/18) is characterized by significant structural changes in corporate bond trading, contrasting sharply with the relatively moderate and seasonally explainable shifts seen in the control periods (2016/17 and 2018/19). While volumes, prices, yields and profits in both control periods displayed relatively stable patterns at the turn of the year, the 2017/18 data reflect an exceptional market response linked to the implementation of regulatory measures—most notably MiFID II and the Basel III Leverage Ratio (Bessembinder et al., 2018; Saar et al., 2023).

In terms of raw observations, the 2017/18 period stands out with 12,326 trades, compared to 10,827 in 2016/17 and 10,183 in 2018/19. Typically, monthly totals lie between 5,000 and 5,500 trades, but January 2018 recorded 7,350 trades, indicating a significant regulatory impact. Conversely, December 2017 registered only 4,976 trades, the lowest monthly total observed. This pattern suggests strategic behavior, as participants may have deferred trades until January 2018 to capitalize on improved post-implementation conditions (Goldstein et al., 2007; Hendershott et al., 2011).

A similar dynamic emerges in the analysis of outliers. In both control periods, around 1,000 outlier trades per month were identified. However, December 2017—a month before the regulations took effect—featured only 802 outlier trades, while January 2018 saw a substantial jump to 1,392 outlier trades, the highest absolute and relative number across all examined periods. This indicates deliberate avoidance of large-volume trades in December 2017, anticipating better conditions in January 2018. Notably, in both control periods, outlier observations tended to decrease at the turn of the year, underscoring the exceptional nature of the 2017/18 regulatory influence.

Over time, the proportion of matchmaking trades generally declined, except for January 2018, which recorded the highest number of matchmaking trades across all periods. Rather than signaling diminishing attractiveness, this pattern implies that matchmaking became more efficient and technologically advanced over time. In the second control period (2018/19), fewer matchmaking trades were observed in absolute terms, but time-to-execution differences were shorter. Across all intervals, zero- and one-second time differences were most common, and relatively speaking, they occurred most frequently in 2018/19. This steady decline in time differences from 2016/17 to 2017/18 and further to 2018/19 suggests that future research could consider zero- and one-second intervals as proxies for ongoing technological improvements in matching efficiency. Such developments highlight the need to periodically reassess and potentially reduce the time cutoff that distinguishes market-making from matchmaking as conditions evolve.

4.2 Hypothesis 1: Market-Making vs. Matchmaking Post-Regulation

Hypothesis 1 posits that market-making trades initially exhibit larger trading volumes, higher prices, yields and profits, reflecting the liquidity and immediacy market-makers provide. In contrast, matchmaking trades, being less capital-intensive, were expected to have smaller volumes, more stable prices, lower yields and lower profits. After regulation, however, a significant share of trading volume should shift from market-making to matchmaking, increasing matchmaking's volumes and profitability, while market-making compensates through higher prices and yields. The analysis relies primarily on Tables 3–10 in the appendix.

Market-making prices remained consistently higher than matchmaking prices across all periods and datasets, affirming the existence of a liquidity premium for market-making—a well-documented phenomenon in financial markets where liquidity providers command higher prices as compensation for immediate trade execution (Amihud et al., 2005). For instance, in the main observation period (2017/18), market-making prices in the full dataset exceeded matchmaking prices by a noticeable margin across both outlier and non-outlier subsets. This premium persisted in control periods, albeit with less pronounced shifts, indicating that market-makers retained some pricing power even as conditions changed. These observations align with Hypothesis 1, confirming that market-making prices were indeed higher, as anticipated due to the liquidity premium associated with their role

In terms of trading volumes, a surprising observation emerges. Despite matchmaking accounting for a significantly smaller share of absolute trades, it constitutes a considerably larger share of the total volume. This implies that the average volume per trade in matchmaking is substantially higher than in market-making, challenging the initial expectation of smaller trade sizes in matchmaking.

Yield patterns, however, also defy initial expectations. Instead of market-making yields surpassing those in matchmaking, the data consistently show higher yields for matchmaking trades across all datasets and time intervals. This is a pivotal and unexpected finding. Since profit is determined by the product of volume, price and yield, the consistently higher yields in matchmaking trades outweigh the lower prices compared to market-making trades. As a result, the yield effect dominates the price effect, leading to a higher-than-expected profit-to-volume ratio for matchmaking trades.

A closer look at numerical comparisons clarifies this point. Across the entire dataset of 33,336 observations combining all periods, matchmaking accounts for only 7.55% of all trades, but represents 33.84% of total volume and 36.84% of total profit. Considering Hypothesis 1 predicted that market-making would handle larger volumes and secure higher yields, these figures are surprising.

Breaking results down by subsets amplifies this understanding. The non-outlier subset consists of 27,054 observations (81.16% of the total), where matchmaking constitutes just 4.04% of trades but captures 4.48% of volume and 4.99% of profit. The volume-to-profit relationship in this subset resembles that of the entire dataset, but the yield gap is slightly larger, reducing matchmaking's relative profit contribution compared to the outlier subset.

In the outlier subset, which contains 6,282 observations (18.84% of the total), large trades dominate, accounting for 86.42% of total volume and 86.73% of total profit. Within this subset, matchmaking represents 22.67% of trades, 38.45% of volume and 41.70% of profit. Although these figures appear strong, the incremental profit advantage for matchmaking is smaller here than in the non-outlier subset. This suggests that as trade sizes grow, the yield difference between matchmaking and market-making narrows, limiting further profit advantages for matchmaking in very large trades.

Over time, prices show a general downward trend across all datasets, reflecting the combined effects of technology, more efficient matching and emerging electronic platforms (Hendershott et al., 2011; Saar et al., 2023). However, December 2017 stands out as an anomaly in this trend, mirroring the patterns observed in absolute trade counts and outliers. Prices in December 2017 were unexpectedly higher than those in December 2016 across the full dataset, the non-outlier subset and for matchmaking trades within the outlier subset. While these differences were moderate, they became more pronounced when comparing January 2017 and January 2018. This strategic delay (participants holding trades until after the regulatory changes) contributed to a notable price and volume shift in January 2018. A possible explanation is that as conditions improved, bank-affiliated dealers, unable to pass increased costs onto customers without risking market share, may have aggressively lowered matchmaking prices to attract customers. Meanwhile, nonbank-affiliated dealers, benefiting from comparative cost advantages, could have intensified their focus on market-making, reinforcing complex competitive dynamics. These dynamics align with theoretical insights from Saar et al. (2023), which suggest that regulatory constraints can create such shifts. This could have contributed to improvements observed in both market-making and matchmaking.

Compared to the extreme price changes in 2017/18 the price changes in 2018/19 are again relatively small. Market-making prices in the non-outlier subset rose slightly, while those in the outlier subset fell, but because the outlier subset dominates in volume terms, the aggregated market-making price ultimately declined. A similar but opposite effect occurred for matchmaking: even though price movements differed between subsets, the larger volume share of outliers led to an overall aggregated price increase for matchmaking.

Hypothesis 1's core expectations find partial support. Market-making retains its price advantage, driven by the liquidity premium and accounts for a larger share of total trading volume, aligning with predictions. However, matchmaking trades, despite representing a smaller proportion of trades, exhibit significantly higher average trade volumes, contradicting the expectation of smaller volumes. Matchmaking yields also surpass market-making yields, which, combined with larger average trade volumes, results in a stronger profit-to-volume ratio for matchmaking. While market-making maintains an absolute profit advantage, regulatory changes have shifted trading dynamics, enabling matchmaking to capture a notable share of profitability. Notably, in the non-outlier dataset, matchmaking achieves higher profit-to-volume ratios compared to the outlier dataset, reflecting its relative efficiency in smaller to medium trade sizes.

4.3 Differences in Dealer Types

The following section aims to investigate the findings from Hypothesis 1 in greater detail, focusing specifically on the different dealer types. The findings are primarily derived from Tables 11–21 in the appendix.

Interdealer trades dominate across all three periods, accounting for 92.97% of all trades, 91.20% of the total volume and 90.90% of total profits. Despite this dominance, interdealer trades exhibit slightly lower average volumes and profits compared to the other dealer types. This observation is noteworthy as interdealers not only account for the majority of trades in absolute terms but also show the highest relative share of matchmaking trades, which are typically associated with higher yields. In contrast, consumer trades account for 6.35% of all trades, while non-member affiliate trades represent only 0.67%, making their market role marginal. Due to this limited representation, the subsequent analysis focuses on the differences between interdealer and consumer trades.

The price analysis reveals that, in both the full dataset and the outlier dataset, market-making prices are consistently higher than matchmaking prices across all dealer types. Consumer trades exhibit the most pronounced differences between market-making and matchmaking prices: market-making prices for consumer trades are consistently higher than those for interdealer trades (with the exception of January 2019), while matchmaking prices for consumer trades are consistently lower than those for interdealer trades. A particularly notable observation is the minimal price difference between interdealer and consumer trades in January 2018, especially in matchmaking. This can be attributed to interdealer trades significantly reducing matchmaking prices compared to the previous month, while consumer trades experienced a slight increase in matchmaking prices during the same period. Interestingly, in the non-outlier dataset, consumer trade prices consistently exceed those of interdealer trades.

A closer analysis of the yields for each dealer confirms that matchmaking yields are always higher than market-making yields. For consumer trades, matchmaking yields are also consistently higher than those for interdealer trades, with the smallest difference observed in January 2018. In the non-outlier dataset, however, market-making and matchmaking yields for consumer trades are significantly lower than the corresponding yields for interdealer trades (with the exception of January 2019). Therefore, the higher prices for smaller volumes cannot be solely attributed to search costs or indirect access to wholesale and interdealer markets, which allow consumer dealers to charge higher prices due to market power (Dunne et al., 2015). Instead, the significantly lower yields, despite higher prices, suggest that relative fixed costs and search costs dominate for consumer dealers, leaving them no choice but to charge higher prices.

Trading volumes and profits show a significant increase for both consumer and interdealer trades over the 2017/18 year-end period, particularly in the area of matchmaking. December 2017 marks the month with the lowest trading volumes and profits for both groups. While the absolute volumes and profits of consumer trades remained nearly unchanged between January 2017 and January 2018, the total volume of interdealer trades increased by 68.03% during the same period and profits surged by an impressive 131.96%. This stark difference is particularly noteworthy as it can be explained by the substantial rise in yield levels, despite falling prices. The shift towards matchmaking trades with significantly higher yields played a pivotal role in this development.

The findings underscore that interdealer trades have benefited significantly from regulatory changes such as MiFID II and the Basel III Leverage Ratio, leveraging their greater market power and adaptability. These changes allowed interdealers to strategically align their business models with the new market conditions, achieving higher profits through a focus on matchmaking trades. At the same time, the data reveal that consumer trades, particularly in the non-outlier dataset, have gained prominence. While interdealers concentrated more on the more profitable matchmaking segment, consumer trades increasingly established themselves as an essential part of smaller market-making trades.

4.4 Differences in Trade Groups

This section aims to investigate the findings from Hypothesis 1 more specifically, focusing on the trade groups. The analysis is based primarily on Tables 22-32 in the appendix.

The number of trades decreases as the trade group size increases, while the total volume exhibits the opposite trend. Block trades, for instance, account for only 3.08% of all trades but represent 49.70% of the total volume and contribute 54.29% of the total profit, resulting in a notably higher profit-to-volume ratio. For all other trade groups, this ratio is negative. All trade groups experienced increases in total volumes and profits at the 2017/18 year-end across both market-making and matchmaking trades. Notably, the relative growth in volumes and profits is larger for higher trade groups, further emphasizing the trend that larger trade groups contribute a higher share to matchmaking. For example, while micro trades maintain a matchmaking share below 0.01% across all periods, block trades contribute 48.41% to matchmaking. Additionally, round-lot and particularly block trades exhibited stronger increases in matchmaking volumes, whereas micro and odd-lot trades showed more pronounced growth in market-making.

The analysis of prices and yields across trade sizes further reveals important patterns. In the full dataset, market-making prices generally decline with increasing trade size: micro trades have the highest prices, followed by odd-lot, round-lot and block trades. However, there are exceptions, such as in January 2017, when block trade market-making prices were higher than those for odd-lot and round-lot trades. Matchmaking prices follow a similar trend, with larger trade sizes associated with lower prices, except in January 2016, when odd-lot trades unexpectedly had lower matchmaking prices than round-lot trades. After January 2018, the price spread between market-making and matchmaking widened considerably, likely reflecting the regulatory changes.

Regarding yields, a clear shift is observed before and after regulation. Before regulation, micro and block trades (extremely small and large trades) consistently had higher matchmaking yields than market-making yields, while odd-lot and round-lot trades (medium-sized trades) exhibited the opposite trend. After regulation, matchmaking yields exceeded market-making yields across all trade groups. While in December 2016 the market-making yield for block trades was the lowest among all yields, it increased sharply in December 2017, surpassing all other yields except for the matchmaking yield of block trades. This increase can be attributed to the matchmaking yield remaining nearly constant between January 2017 and December 2017, as market participants likely avoided executing larger trades and waited for improved market conditions at the turn of the year from 2017 to 2018. From January 2018 onward, the market-making yield for block trades remained noticeably higher than all other yields, except for the matchmaking yield of block trades, throughout the subsequent observation periods. Odd-lot trades, which had previously outperformed round-lot trades in yield, fell behind in 2018, likely due to shifts in trading conditions.

The non-outlier dataset, comprising only micro and odd-lot trades, reveals that micro trades consistently exhibit higher prices than odd-lot trades. Matchmaking yields are consistently higher than market-making yields in this subset and larger trades achieve better yields. In the outlier dataset, patterns largely align with the full dataset, as the characteristics of block and round-lot trades dominate, overshadowing the smaller trade volumes represented in the non-outlier dataset.

These findings underscore how trade size and regulation influence price and yield dynamics. Regulatory measures introduced in January 2018 appear to have widened price spreads and reinforced yield hierarchies, particularly benefiting larger trades in matchmaking contexts. This demonstrates the critical role of trade size and market structure in shaping dealer behavior and market outcomes.

4.5 Regression Analysis

The weighted DiD regressions provide detailed insights into the dynamics between market-making and matchmaking across different time periods and data subsets. The explanatory variables—post, price, yield, quantity and counterparty type reveal distinct patterns that align with the descriptive analyses and the proposed hypotheses. The regressions are presented in the appendix (Table 33).

The adjusted R^2 values demonstrate significant variation across datasets and time periods. For the non-outlier data, the R^2 values are consistently below 1%, likely reflecting the more uniform trade volumes and reduced variability compared to the outlier dataset. Conversely, the R^2 values for the entire dataset exceed those of the outlier dataset across all three periods. Surprisingly, the main observation period (2017/18) exhibits the lowest explanatory power despite having the highest number of observations and significant increases in both market-making and matchmaking trades. This may result from simultaneous volume increases in both mechanisms, reducing the explainable variation. In contrast, the second control period (2018/19) shows the highest R^2 values, likely due to the pronounced rise in market-making shares and the decline in matchmaking shares at the turn of the year, resulting in greater variation.

The coefficients for the `post` variable decrease over time, becoming negative in the second control period. This aligns with observed trends: matchmaking volumes rose sharply in 2016/17 while market-making volumes declined, resulting in positive post coefficients. By 2017/18, both mechanisms increased, though matchmaking grew slightly more, leading to smaller positive coefficients. By 2018/19, market-making shares increased while matchmaking shares decreased significantly, resulting in negative coefficients. Notably, the significance levels of the post variable also decrease over time: significant at the 1% level in 2016/17 for the entire dataset and outlier subset, at 5% in 2017/18 and at 10% in 2018/19.

`Price` coefficients are almost uniformly negative across all regressions, confirming earlier findings that market-making trades command a consistent price premium. Higher prices correlate with a lower probability of matchmaking, reinforcing the conclusion that market-making retains its role as the liquidity provider offering stable pricing—fully consistent with Hypothesis 1. While insignificant in 2016/17, price coefficients become significant at the 1% level in most cases for 2017/18 and 2018/19, with increasingly negative values over time. This trend reflects the overall decline in price levels and suggests that price increases in later periods have a larger relative impact.

In contrast to price, `yield` coefficients exhibit an inverse pattern, being consistently positive. Only the 2016/17 period yields significant coefficients, all at the 1% level. These high coefficients correspond to the sharp increase in matchmaking observed during this period. For 2017/18 and 2018/19, coefficients remain largely insignificant, with slightly lower values in 2017/18. The consistently positive coefficients confirm the surprising outcome that matchmaking trades, contrary to initial expectations, exhibit higher yields. These yield advantages make matchmaking a more attractive alternative, particularly under the cost reconfigurations prompted by regulatory pressures.

The `Volume` coefficients are positive across all regressions, with most models showing a very high level of statistical significance. However, their values are extremely small, reflecting the large variation in trade volumes. The lowest coefficients occur in 2017/18, a period marked by the greatest volume variability. The consistently positive coefficients suggest that higher volumes, particularly in round-lot and block trades, are associated with a greater relative share of matchmaking. This aligns with the higher average volumes observed for matchmaking trades compared to market-making trades.

The dummy variable for non-member affiliate trades, relative to interdealer trades, is negative across all nine regressions and significant at the 1% level for the entire and outlier datasets. However, these results should be interpreted cautiously due to the small number of trades involving non-member affiliates, which consistently exhibit the lowest matchmaking-to-market-making ratios among all dealer types. The dummy variable for consumer trades, compared to interdealer trades, is generally positive but insignificant in most regressions. Notably, the coefficients are lowest during the main observation period (2017/18), suggesting that interdealer trades experienced the most pronounced regulatory impact in terms of volume.

In the 2016/17 period, the constant term is not significant at any level and is notably lower compared to subsequent periods. This lower value indicates that the coefficients of the other variables play a relatively larger role in explaining the variation during this period. In contrast, the later periods show substantially higher constant terms, which are significant at the 1% level, indicating a shift in the relative contribution of the constant to the overall model explanation.

In summary, the weighted DiD regressions illuminate the evolving dynamics of market-making and matchmaking, highlighting the regulatory impacts on trade behavior and dealer strategies. The results reveal nuanced shifts in explanatory power, price and yield dynamics and the roles of different counterparty types, offering a robust framework for understanding the interplay between market mechanisms and regulatory interventions. These findings provide valuable insights into the long-term implications for market structure and liquidity provision.

5 Limitations

Despite the comprehensive approach and the robust dataset employed in this analysis, several limitations remain that warrant further consideration in future research.

First, the choice of cutoff values for classifying trades into market-making and matchmaking is subject to refinement. While this study applied a specific time threshold, the rapid advancement of trading technologies suggests that shorter time frames may become increasingly relevant. Over time, improved efficiency in matching processes could render the current cutoff less appropriate. Using alternative thresholds—potentially as low as zero or one second—would help evaluate the robustness of the classification and determine whether the observed yield discrepancies (e.g., matchmaking yields exceeding market-making yields) are the result of misclassification. Such adjustments are particularly important for periods extending beyond the current observation windows, where ongoing technological improvements are likely to reduce search times even further.

Second, the analysis is constrained by its temporal scope and event selection. While the focus on short two-month intervals allowed for an immediate assessment of regulatory impacts, this choice limits the generalizability of the findings. Future studies could examine longer horizons, for instance the full range of several consecutive years rather than isolated December and January samples from multiple years. This expanded timeline would better account for seasonal patterns—such as end-year and start-year effects—and deliver a more stable baseline against which to measure changes in market-making and matchmaking dynamics. Furthermore, examining a global shock period like the COVID-19 pandemic could yield valuable insights into how extreme market conditions affect the composition of market-making and matchmaking, as well as volumes, yields, prices and timing differences.

Third, the dataset employed was restricted to three corporate bonds from firms that had at least 10,000 trades in the main investigation period. While this approach facilitated feasibility and ensured a sizable trade count, it constrains the representativeness of the results. To isolate firm-specific factors, future analyses should consider all traded corporate bonds in the same three periods and compare outcomes. Such expansions could help determine how particular industries, sectors or business lines influence market-making and matchmaking patterns and whether certain types of firms are more or less impacted by regulatory changes.

A further limitation arises from the lack of detailed dealer information. The absence of explicit dealer identifiers meant that trades without matching partners (in terms of profit and bond ID) could not be properly classified, resulting in their exclusion. Similarly, trades with identical profits and bond identifiers might be matched by default, even though they could originate from distinct dealers who—had dealer-specific commissions been available—would likely have shown price differences after adding commissions. Without these commissions, the observed prices might not fully reflect the true cost, potentially skewing interpretations of yields and market dynamics. This issue is particularly pronounced for smaller-volume trades, where multiple apparently identical trades might in fact represent subdivisions of a larger transaction. Access to dealer-level data would mitigate these concerns, reduce misclassifications and allow for a more precise assessment of market-making and matchmaking relationships.

Finally, the absence of dealer characteristics also limits the ability to discern how bank-affiliated versus nonbank-affiliated dealers respond to regulatory changes and how their strategies differ across market conditions. Incorporating detailed dealer-level information could illuminate how these entities adapt their roles in market-making and matchmaking, especially during cyclical phases—such as booms and recessions—and under various shock scenarios. Such insights would enrich the understanding of search frictions, liquidity provision and the evolving landscape of market intermediation.

In conclusion, while this study provides meaningful insights into market-making and matchmaking dynamics following regulatory changes, future research should address these limitations. Refining cutoff thresholds, extending the temporal scope, considering additional corporate bonds and broader firm sets, incorporating dealer-level data and analyzing global shock periods or business cycle variations would all contribute to a more nuanced and complete understanding of the complex interplay between market-making, matchmaking and regulatory interventions.

6 Conclusion

This study provides an in-depth empirical examination of the U.S. corporate bond market's adaptation to regulatory changes, particularly the Basel III Leverage Ratio and MiFID II. By analyzing transaction-level TRACE data, it uncovers nuanced dynamics in market-making and matchmaking mechanisms, focusing on their roles in liquidity provision, price formation and profitability.

Key findings emphasize a significant shift in trade behavior post-regulation. Market-making retained its liquidity premium, characterized by higher prices and immediate execution. However, matchmaking demonstrated unexpected resilience and profitability, with consistently higher yields and a growing share of large trade volumes. This reallocation of trade patterns highlights the interplay between capital efficiency and evolving dealer strategies under regulatory constraints.

The results further reveal the heterogeneity across trade groups and dealer types. Larger trade groups increasingly favored matchmaking, while smaller trades were predominantly market-made. Interdealer trades, although dominant in volume and profit, exhibited relatively lower yields compared to consumer trades, whose higher prices compensated for their constrained market access. These insights underline the role of regulatory interventions in reshaping market structures and encouraging technological advancements in trade execution.

Weighted Difference-in-Differences regression analyses corroborate these observations, confirming the regulatory impact on trade volumes, prices and yields across diverse datasets and periods. Notably, these models highlight the diminishing explanatory power of price variables over time, reflecting the growing efficiency of matchmaking mechanisms.

Despite its contributions, the study acknowledges limitations, such as the lack of dealer-specific data and the narrow temporal scope. Future research should extend these findings by incorporating broader datasets, refining classification thresholds and exploring global shock periods to better understand the resilience and adaptability of market intermediaries under varying conditions.

In conclusion, this research bridges theoretical frameworks and empirical evidence, providing actionable insights for policymakers and market participants. It underscores the critical balance between regulation, liquidity and market efficiency in decentralized markets, advocating for adaptive regulatory frameworks that accommodate ongoing technological and structural shifts.

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A Appendix

Trade Type	Dec 2016	Jan 2017	Dec 2017	Jan 2018	Dec 2018	Jan 2019	Total
Total Market-Making	4,956	4,921	4,624	6,698	4,824	4,796	30,819
Total Matchmaking	431	519	352	652	297	266	2,517
Non-Outlier Market-Making	4,109	4,165	3,995	5,755	3,970	3,967	25,961
Non-Outlier Matchmaking	184	263	180	203	132	131	1,093
Outlier Market-Making	847	756	629	943	854	829	4,858
Outlier Matchmaking	247	256	172	449	165	135	1,424

Table 1: Absolute Trade Frequencies of Different Datasets

Time Difference (in seconds)	Dec 2016	Jan 2017	Dec 2017	Jan 2018	Dec 2018	Jan 2019	Total
0	3,253	3,117	3,148	4,456	3,525	3,440	20,939
1	3,912	3,842	3,780	5,387	4,092	3,999	25,012
60	4,956	4,921	4,624	6,698	4,824	4,796	30,819
300	5,254	5,238	4,889	7,187	5,041	4,991	32,600
900	5,326	5,345	4,939	7,303	5,077	5,031	33,021

Table 2: Absolute Number of Market-Making Trades by Different Time Thresholds

Month	Trade Type	Total Mean	Non-Outlier Mean	Outlier Mean
Dec 2016	Market-Making	98.69	98.92	98.64
	Matchmaking	95.92	95.88	95.92
Jan 2017	Market-Making	100.77	100.91	100.74
	Matchmaking	98.14	100.38	98.10
Dec 2017	Market-Making	98.75	100.93	98.16
	Matchmaking	96.29	98.87	96.22
Jan 2018	Market-Making	95.45	99.54	94.42
	Matchmaking	89.76	96.27	89.66
Dec 2018	Market-Making	94.17	96.34	93.65
	Matchmaking	84.14	95.17	83.98
Jan 2019	Market-Making	93.72	97.86	92.78
	Matchmaking	84.92	92.84	84.76

Table 3: Weighted Prices of Hypothesis 1

Month	Trade Type	Total Mean	Non-Outlier Mean	Outlier Mean
Dec 2016	Market-Making	3.59	4.58	3.36
	Matchmaking	4.46	5.40	4.44
Jan 2017	Market-Making	3.70	4.13	3.60
	Matchmaking	4.40	4.58	4.40
Dec 2017	Market-Making	4.28	4.29	4.27
	Matchmaking	4.49	5.16	4.47
Jan 2018	Market-Making	5.42	4.84	5.57
	Matchmaking	6.39	5.57	6.40
Dec 2018	Market-Making	5.37	5.04	5.45
	Matchmaking	7.63	5.37	7.66
Jan 2019	Market-Making	5.66	4.74	5.87
	Matchmaking	8.11	6.21	8.15

Table 4: Weighted Yields of Hypothesis 1

Trade Type	Dec 2016	Jan 2017	Dec 2017	Jan 2018	Dec 2018	Jan 2019	Total
Market-Making	498,403,000	444,656,500	458,763,000	785,742,000	430,349,000	438,773,000	3,056,686,500
Matchmaking	253,339,000	332,601,000	169,692,000	467,779,000	205,227,000	134,946,000	1,563,584,000

Table 5: Total Volumes of Market-Making vs. Matchmaking

Trade Type	Dec 2016	Jan 2017	Dec 2017	Jan 2018	Dec 2018	Jan 2019	Total
Market-Making	1,711,767,917	1,633,622,637	1,849,387,457	3,959,937,589	2,049,749,303	2,176,808,484	13,380,173,387
Matchmaking	1,045,092,315	1,388,503,567	698,958,952	2,598,567,722	1,203,612,529	868,836,784	7,803,571,869

Table 6: Total Profits of Market-Making vs. Matchmaking

Trade Type	Dec 2016	Jan 2017	Dec 2017	Jan 2018	Dec 2018	Jan 2019	Total
Market-Making	91,388,000	86,398,500	98,405,000	158,314,000	83,076,000	81,571,000	599,152,500
Matchmaking	4,823,000	5,396,000	4,668,000	7,358,000	3,060,000	2,801,000	28,106,000

Table 7: Non-Outlier Volumes of Market-Making vs. Matchmaking

Trade Type	Dec 2016	Jan 2017	Dec 2017	Jan 2018	Dec 2018	Jan 2019	Total
Market-Making	403,055,626	353,249,794	415,011,996	744,970,116	385,287,945	364,557,866	2,666,133,343
Matchmaking	24,312,408	24,391,126	23,142,321	38,342,586	14,829,259	15,151,064	140,168,764

Table 8: Non-Outlier Profits of Market-Making vs. Matchmaking

Trade Type	Dec 2016	Jan 2017	Dec 2017	Jan 2018	Dec 2018	Jan 2019	Total
Market-Making	407,015,000	358,258,000	360,358,000	627,428,000	347,273,000	357,202,000	2,457,534,000
Matchmaking	248,516,000	327,205,000	165,024,000	460,421,000	202,167,000	132,145,000	1,535,478,000

Table 9: Outlier Volumes of Market-Making vs. Matchmaking

Trade Type	Dec 2016	Jan 2017	Dec 2017	Jan 2018	Dec 2018	Jan 2019	Total
Market-Making	1,308,712,291	1,280,372,843	1,434,375,461	3,214,967,473	1,664,461,358	1,812,250,617	10,715,139,043
Matchmaking	1,020,779,907	1,364,112,441	675,816,631	2,560,225,136	1,188,783,270	853,685,720	7,663,403,105

Table 10: Outlier Profits of Market-Making vs. Matchmaking

Dealer Type	Trade Type	Dec 2016	Jan 2017	Dec 2017	Jan 2018	Dec 2018	Jan 2019	Total
Non-member affiliate	Market-Making	10	34	22	65	44	43	218
	Matchmaking	1	1	1	2	1	0	6
Consumer	Market-Making	249	272	299	415	385	375	1,995
	Matchmaking	25	27	12	27	14	18	123
Interdealer	Market-Making	4,697	4,615	4,303	6,218	4,395	4,378	28,606
	Matchmaking	405	491	339	623	282	248	2,388

Table 11: Absolute Trade Frequencies of All Dealer Types

Dealer Type	Trade Type	Dec 2016	Jan 2017	Dec 2017	Jan 2018	Dec 2018	Jan 2019	Total
Non-member affiliate	Market-Making	4	18	9	32	23	24	110
	Matchmaking	1	1	1	0	1	0	4
Consumer	Market-Making	231	235	281	382	343	327	1,799
	Matchmaking	11	14	6	0	8	8	59
Interdealer	Market-Making	3,874	3,912	3,705	5,341	3,604	3,616	24,052
	Matchmaking	172	248	173	0	124	123	1,030

Table 12: Absolute Trade Frequencies of Non-Outlier Dealer Types

Dealer Type	Trade Type	Dec 2016	Jan 2017	Dec 2017	Jan 2018	Dec 2018	Jan 2019	Total
Non-member affiliate	Market-Making	6	16	13	33	21	19	108
	Matchmaking	0	0	0	1	1	0	2
Consumer	Market-Making	18	37	18	33	42	48	196
	Matchmaking	14	13	6	15	6	10	64
Interdealer	Market-Making	823	703	598	877	791	762	4,554
	Matchmaking	233	243	166	433	158	125	1,358

Table 13: Absolute Trade Frequencies of Outlier Dealer Types

Month	Dealer Type	Trade Type	Total Mean	Non-Outlier Mean	Outlier Mean
Dec 2016	Non-member affiliate	Market-Making	99.29	101.22	99.25
		Matchmaking	98.75	98.75	N/A
	Consumer	Market-Making	100.40	102.09	99.94
		Matchmaking	91.45	100.46	91.40
	Interdealer	Market-Making	98.61	98.76	98.58
		Matchmaking	96.76	95.68	96.78
Jan 2017	Non-member affiliate	Market-Making	104.06	102.97	104.09
		Matchmaking	100.86	100.86	N/A
	Consumer	Market-Making	102.91	102.05	103.03
		Matchmaking	85.57	101.22	85.36
	Interdealer	Market-Making	100.29	100.84	100.14
		Matchmaking	99.07	100.33	99.05
Dec 2017	Non-member affiliate	Market-Making	99.95	97.97	100.02
		Matchmaking	93.00	93.00	N/A
	Consumer	Market-Making	101.37	102.04	101.16
		Matchmaking	88.50	102.44	88.35
	Interdealer	Market-Making	98.58	100.88	97.94
		Matchmaking	96.76	98.80	96.70
Jan 2018	Non-member affiliate	Market-Making	94.38	99.90	94.20
		Matchmaking	88.10	89.02	88.06
	Consumer	Market-Making	98.29	101.55	97.27
		Matchmaking	88.94	100.50	88.86
	Interdealer	Market-Making	95.37	99.42	94.30
		Matchmaking	89.81	96.21	89.70
Dec 2018	Non-member affiliate	Market-Making	95.99	94.43	96.04
		Matchmaking	100.85	N/A	N/A
	Consumer	Market-Making	97.12	99.03	96.49
		Matchmaking	72.73	100.23	72.35
	Interdealer	Market-Making	93.88	96.13	93.33
		Matchmaking	84.86	94.85	84.70
Jan 2019	Non-member affiliate	Market-Making	100.10	99.51	100.14
		Matchmaking	N/A	N/A	N/A
	Consumer	Market-Making	91.71	99.67	89.08
		Matchmaking	79.37	93.38	79.24
	Interdealer	Market-Making	93.73	97.70	92.84
		Matchmaking	85.72	92.81	85.55

Table 14: Weighted Prices of Dealer Types

Month	Dealer Type	Trade Type	Total Mean	Non-Outlier Mean	Outlier Mean
Dec 2016	Non-member affiliate	Market-Making	1.97	4.83	1.91
		Matchmaking	5.03	5.03	N/A
	Consumer	Market-Making	2.57	3.39	2.35
		Matchmaking	5.07	3.85	5.08
	Interdealer	Market-Making	3.65	4.64	3.42
		Matchmaking	4.35	5.47	4.32
Jan 2017	Non-member affiliate	Market-Making	4.08	3.10	4.10
		Matchmaking	5.93	5.93	N/A
	Consumer	Market-Making	3.69	3.39	3.73
		Matchmaking	6.80	3.53	6.85
	Interdealer	Market-Making	3.67	4.17	3.53
		Matchmaking	4.23	4.64	4.22
Dec 2017	Non-member affiliate	Market-Making	4.24	3.00	4.29
		Matchmaking	8.25	8.25	N/A
	Consumer	Market-Making	2.66	3.59	2.36
		Matchmaking	5.98	4.44	5.99
	Interdealer	Market-Making	4.36	4.33	4.37
		Matchmaking	4.40	5.17	4.38
Jan 2018	Non-member affiliate	Market-Making	5.54	4.63	5.57
		Matchmaking	7.36	7.19	7.37
	Consumer	Market-Making	3.99	3.51	4.14
		Matchmaking	6.58	3.46	6.61
	Interdealer	Market-Making	5.48	4.91	5.63
		Matchmaking	6.37	5.61	6.39
Dec 2018	Non-member affiliate	Market-Making	5.47	5.36	5.47
		Matchmaking	4.24	4.24	N/A
	Consumer	Market-Making	4.59	3.82	4.84
		Matchmaking	11.12	3.35	11.23
	Interdealer	Market-Making	5.41	5.14	5.48
		Matchmaking	7.40	5.49	7.43
Jan 2019	Non-member affiliate	Market-Making	4.60	3.49	4.69
		Matchmaking	N/A	N/A	N/A
	Consumer	Market-Making	6.44	3.89	7.28
		Matchmaking	9.19	6.24	9.22
	Interdealer	Market-Making	5.63	4.82	5.82
		Matchmaking	7.95	6.21	7.99

Table 15: Weighted Yields of Dealer Types

Dealer Type	Trade Type	Dec 2016	Jan 2017	Dec 2017	Jan 2018	Dec 2018	Jan 2019	Total
Non-member affiliate	Market-Making	4,795,000	32,293,000	11,054,000	39,816,000	19,614,000	7,079,000	114,651,000
	Matchmaking	25,000	10,000	10,000	1,039,000	1,000,000	0	2,084,000
Consumer	Market-Making	19,823,000	34,589,000	23,021,000	34,446,000	25,898,000	24,423,000	162,200,000
	Matchmaking	40,042,000	22,805,000	9,714,000	22,902,000	13,427,000	16,832,000	125,722,000
Interdealer	Market-Making	473,785,000	377,774,500	424,688,000	711,480,000	384,837,000	407,271,000	2,779,835,500
	Matchmaking	213,272,000	309,786,000	159,968,000	443,838,000	190,800,000	118,114,000	1,435,778,000

Table 16: Total Volumes of Dealer Types: Market-Making vs. Matchmaking

Dealer Type	Trade Type	Dec 2016	Jan 2017	Dec 2017	Jan 2018	Dec 2018	Jan 2019	Total
Non-member affiliate	Market-Making	9,387,695	137,647,301	46,283,881	204,973,080	100,557,856	32,412,636	531,262,449
	Matchmaking	124,144	59,836	76,682	6,735,498	4,280,209	0	11,276,369
Consumer	Market-Making	50,639,028	132,022,896	61,735,037	132,755,258	111,760,229	133,119,031	622,031,479
	Matchmaking	177,385,172	130,517,121	50,317,628	132,282,197	107,504,662	117,241,424	715,248,204
Interdealer	Market-Making	1,651,741,193	1,363,952,440	1,741,368,539	3,622,209,251	1,837,431,218	2,011,276,817	12,228,179,458
	Matchmaking	867,582,999	1,257,926,610	648,564,642	2,459,550,027	1,091,827,658	751,595,360	7,077,046,296

Table 17: Total Profits of Dealer Types: Market-Making vs. Matchmaking

Dealer Type	Trade Type	Dec 2016	Jan 2017	Dec 2017	Jan 2018	Dec 2018	Jan 2019	Total
Non-member affiliate	Market-Making	96,000	729,000	353,000	1,316,000	652,000	519,000	3,665,000
	Matchmaking	25,000	10,000	10,000	39,000	0	0	84,000
Consumer	Market-Making	4,203,000	4,018,000	5,647,000	8,249,000	6,362,000	6,061,000	34,540,000
	Matchmaking	192,000	302,000	105,000	160,000	181,000	157,000	1,097,000
Interdealer	Market-Making	87,089,000	81,651,500	92,405,000	148,749,000	76,062,000	74,991,000	560,947,500
	Matchmaking	4,606,000	5,084,000	4,553,000	7,159,000	2,879,000	2,644,000	26,925,000

Table 18: Non-Outlier Volumes of Dealer Types: Market-Making vs. Matchmaking

Dealer Type	Trade Type	Dec 2016	Jan 2017	Dec 2017	Jan 2018	Dec 2018	Jan 2019	Total
Non-member affiliate	Market-Making	456,455	2,338,188	1,018,292	5,994,292	3,045,674	1,798,691	14,651,592
	Matchmaking	124,144	59,836	76,682	249,549	0	0	510,211
Consumer	Market-Making	14,444,556	13,784,326	20,453,552	29,174,111	23,688,934	23,158,335	124,703,814
	Matchmaking	743,016	1,077,817	476,555	554,135	608,576	865,934	4,326,033
Interdealer	Market-Making	388,154,615	337,127,279	393,540,153	709,801,713	358,553,337	339,600,841	2,526,777,938
	Matchmaking	23,445,249	23,253,473	22,589,083	37,538,902	14,220,684	14,285,131	135,332,522

Table 19: Non-Outlier Profits of Dealer Types: Market-Making vs. Matchmaking

Dealer Type	Trade Type	Dec 2016	Jan 2017	Dec 2017	Jan 2018	Dec 2018	Jan 2019	Total
Non-member affiliate	Market-Making	4,699,000	31,564,000	10,701,000	38,500,000	18,962,000	6,560,000	110,986,000
	Matchmaking	0	0	0	1,000,000	1,000,000	0	2,000,000
Consumer	Market-Making	15,620,000	30,571,000	17,374,000	26,197,000	19,536,000	18,362,000	127,660,000
	Matchmaking	39,850,000	22,503,000	9,609,000	22,742,000	13,246,000	16,675,000	124,625,000
Interdealer	Market-Making	386,696,000	296,123,000	332,283,000	562,731,000	308,775,000	332,280,000	2,218,888,000
	Matchmaking	208,666,000	304,702,000	155,415,000	436,679,000	187,921,000	115,470,000	1,408,853,000

Table 20: Outlier Volumes of Dealer Types: Market-Making vs. Matchmaking

Dealer Type	Trade Type	Dec 2016	Jan 2017	Dec 2017	Jan 2018	Dec 2018	Jan 2019	Total
Non-member affiliate	Market-Making	8,931,240	135,309,113	45,265,589	198,978,787	97,512,182	30,613,945	516,610,856
	Matchmaking	0	0	0	6,485,950	4,280,209	0	10,766,159
Consumer	Market-Making	36,194,473	118,238,570	41,281,485	103,581,147	88,071,295	109,960,696	497,327,666
	Matchmaking	176,642,157	129,439,304	49,841,073	131,728,061	106,896,087	116,375,490	710,922,172
Interdealer	Market-Making	1,263,586,578	1,026,825,160	1,347,828,386	2,912,407,538	1,478,877,882	1,671,675,976	9,701,201,520
	Matchmaking	844,137,751	1,234,673,137	625,975,558	2,422,011,125	1,077,606,975	737,310,230	6,941,714,776

Table 21: Outlier Profits of Dealer Types: Market-Making vs. Matchmaking

Trade Group	Trade Type	Dec 2016	Jan 2017	Dec 2017	Jan 2018	Dec 2018	Jan 2019	Total
Micro	Market-Making	2,769	3,052	2,735	3,632	2,722	2,832	17,742
	Matchmaking	99	192	118	112	90	86	697
Odd-lot	Market-Making	1,907	1,589	1,551	2,434	1,729	1,605	10,815
	Matchmaking	154	134	95	124	69	70	646
Round-lot	Market-Making	221	232	269	436	307	277	1,742
	Matchmaking	111	111	93	233	71	48	667
Block	Market-Making	59	48	69	196	66	82	520
	Matchmaking	67	82	46	183	67	62	507

Table 22: Absolute Trade Frequencies of All Trade Groups

Trade Group	Trade Type	Dec 2016	Jan 2017	Dec 2017	Jan 2018	Dec 2018	Jan 2019	Total
Micro	Market-Making	2,764	3,052	2,735	3,632	2,722	2,831	17,736
	Matchmaking	99	192	118	112	90	86	697
Odd-lot	Market-Making	1,345	1,113	1,260	2,123	1,248	1,136	8,225
	Matchmaking	85	71	62	91	42	45	396

Table 23: Absolute Trade Frequencies of Non-Outlier Trade Groups

Trade Group	Trade Type	Dec 2016	Jan 2017	Dec 2017	Jan 2018	Dec 2018	Jan 2019	Total
Micro	Market-Making	5	0	0	0	0	1	6
	Matchmaking	0	0	0	0	0	0	0
Odd-lot	Market-Making	562	476	291	311	481	469	2,590
	Matchmaking	69	63	33	33	27	25	250
Round-lot	Market-Making	221	232	269	436	307	277	1,742
	Matchmaking	111	111	93	233	71	48	667
Block	Market-Making	59	48	69	196	66	82	520
	Matchmaking	67	82	46	183	67	62	507

Table 24: Absolute Trade Frequencies of Outlier Trade Groups

Month	Trade Group	Trade Type	Total Mean	Non-Outlier Mean	Outlier Mean
Dec 2016	Micro	Market-Making	101.89	101.92	100.04
		Matchmaking	100.55	N/A	N/A
	Odd-lot	Market-Making	99.12	97.02	100.34
		Matchmaking	98.65	94.41	99.78
	Round-lot	Market-Making	98.90	N/A	98.90
		Matchmaking	99.17	N/A	99.17
	Block	Market-Making	97.57	N/A	97.57
		Matchmaking	94.15	N/A	94.15
Jan 2017	Micro	Market-Making	102.62	102.62	N/A
		Matchmaking	103.22	103.22	N/A
	Odd-lot	Market-Making	100.34	99.50	100.84
		Matchmaking	100.71	98.46	101.36
	Round-lot	Market-Making	99.29	N/A	99.29
		Matchmaking	99.19	N/A	99.19
	Block	Market-Making	101.93	N/A	101.93
		Matchmaking	97.62	N/A	97.62
Dec 2017	Micro	Market-Making	102.22	102.22	N/A
		Matchmaking	102.30	102.30	N/A
	Odd-lot	Market-Making	101.04	100.29	101.86
		Matchmaking	99.88	97.85	100.79
	Round-lot	Market-Making	98.23	N/A	98.23
		Matchmaking	97.11	N/A	97.11
	Block	Market-Making	96.82	N/A	96.82
		Matchmaking	95.41	N/A	95.41
Jan 2018	Micro	Market-Making	102.22	102.22	N/A
		Matchmaking	101.62	101.62	N/A
	Odd-lot	Market-Making	99.50	98.49	101.37
		Matchmaking	98.73	95.12	102.32
	Round-lot	Market-Making	96.87	N/A	96.87
		Matchmaking	95.14	N/A	95.14
	Block	Market-Making	92.05	N/A	92.05
		Matchmaking	87.49	N/A	87.49
Dec 2018	Micro	Market-Making	98.55	98.55	N/A
		Matchmaking	98.13	98.13	N/A
	Odd-lot	Market-Making	96.56	94.96	97.79
		Matchmaking	95.50	93.50	96.47
	Round-lot	Market-Making	93.57	N/A	93.57
		Matchmaking	91.04	N/A	91.04
	Block	Market-Making	91.85	N/A	91.85
		Matchmaking	82.08	N/A	82.08
Jan 2019	Micro	Market-Making	99.41	99.41	100.04
		Matchmaking	98.72	98.72	N/A
	Odd-lot	Market-Making	97.99	96.80	98.83
		Matchmaking	96.71	89.96	99.61
	Round-lot	Market-Making	95.39	N/A	95.39
		Matchmaking	90.74	N/A	90.74
	Block	Market-Making	87.84	N/A	87.84
		Matchmaking	82.93	N/A	82.93

Table 25: Weighted Prices of Trade Groups

Month	Trade Group	Trade Type	Total Mean	Non-Outlier Mean	Outlier Mean
Dec 2016	Micro	Market-Making	3.21	3.24	0.97
		Matchmaking	3.81	3.81	N/A
	Odd-lot	Market-Making	3.98	5.43	3.15
		Matchmaking	3.77	5.90	3.20
	Round-lot	Market-Making	3.78	N/A	3.78
		Matchmaking	3.77	N/A	3.77
	Block	Market-Making	3.19	N/A	3.19
		Matchmaking	4.85	N/A	4.85
Jan 2017	Micro	Market-Making	2.98	2.98	N/A
		Matchmaking	3.26	3.26	N/A
	Odd-lot	Market-Making	3.87	5.07	3.15
		Matchmaking	3.72	5.48	3.22
	Round-lot	Market-Making	3.87	N/A	3.87
		Matchmaking	3.83	N/A	3.83
	Block	Market-Making	3.60	N/A	3.60
		Matchmaking	4.63	N/A	4.63
Dec 2017	Micro	Market-Making	3.22	3.22	N/A
		Matchmaking	3.42	3.42	N/A
	Odd-lot	Market-Making	3.90	4.83	2.90
		Matchmaking	3.68	5.68	2.78
	Round-lot	Market-Making	4.45	N/A	4.45
		Matchmaking	4.40	N/A	4.40
	Block	Market-Making	4.61	N/A	4.61
		Matchmaking	4.64	N/A	4.64
Jan 2018	Micro	Market-Making	3.33	3.33	N/A
		Matchmaking	3.37	3.37	N/A
	Odd-lot	Market-Making	4.62	5.42	3.14
		Matchmaking	4.76	6.04	3.48
	Round-lot	Market-Making	5.01	N/A	5.01
		Matchmaking	5.40	N/A	5.40
	Block	Market-Making	6.25	N/A	6.25
		Matchmaking	6.80	N/A	6.80
Dec 2018	Micro	Market-Making	3.99	3.99	N/A
		Matchmaking	4.14	4.14	N/A
	Odd-lot	Market-Making	4.81	5.69	4.14
		Matchmaking	5.26	6.06	4.87
	Round-lot	Market-Making	5.38	N/A	5.38
		Matchmaking	5.87	N/A	5.87
	Block	Market-Making	6.10	N/A	6.10
		Matchmaking	8.13	N/A	8.13
Jan 2019	Micro	Market-Making	3.84	3.85	0.68
		Matchmaking	4.03	4.03	N/A
	Odd-lot	Market-Making	4.56	5.35	4.00
		Matchmaking	4.75	7.28	3.66
	Round-lot	Market-Making	5.11	N/A	5.11
		Matchmaking	6.80	N/A	6.80
	Block	Market-Making	7.37	N/A	7.37
		Matchmaking	8.61	N/A	8.61

Table 26: Weighted Yields of Trade Groups

Trade Group	Trade Type	Dec 2016	Jan 2017	Dec 2017	Jan 2018	Dec 2018	Jan 2019	Total
Micro	Market-Making	35,933,000	39,116,500	32,898,000	44,404,000	31,883,000	33,122,000	217,356,500
	Matchmaking	1,159,000	2,180,000	1,074,000	1,300,000	1,104,000	921,000	7,738,000
Odd-lot	Market-Making	152,549,000	125,814,000	125,396,000	175,615,000	117,995,000	116,914,000	814,283,000
	Matchmaking	17,404,000	14,437,000	11,559,000	12,155,000	5,975,000	6,255,000	67,785,000
Round-lot	Market-Making	125,891,000	129,631,000	127,856,000	189,396,000	133,998,000	133,911,000	840,683,000
	Matchmaking	72,321,000	74,705,000	52,702,000	118,696,000	36,401,000	21,530,000	376,355,000
Block	Market-Making	184,030,000	150,095,000	172,613,000	376,327,000	146,473,000	154,826,000	1,184,364,000
	Matchmaking	162,455,000	241,279,000	104,357,000	335,628,000	161,747,000	106,240,000	1,111,706,000

Table 27: Total Volumes of Trade Groups: Market-Making vs. Matchmaking

Trade Group	Trade Type	Dec 2016	Jan 2017	Dec 2017	Jan 2018	Dec 2018	Jan 2019	Total
Micro	Market-Making	115,654,345	119,162,822	107,106,310	150,193,033	122,985,828	124,198,186	739,787,524
	Matchmaking	4,359,321	7,348,470	3,720,644	4,385,662	4,367,588	3,540,232	27,721,917
Odd-lot	Market-Making	585,719,155	480,159,561	482,781,093	789,070,220	526,670,083	504,172,144	3,368,572,256
	Matchmaking	62,839,153	53,383,090	41,614,147	55,319,532	28,565,658	27,365,748	269,087,328
Round-lot	Market-Making	457,428,580	486,807,779	538,098,123	894,478,420	633,021,554	615,493,394	3,625,327,850
	Matchmaking	264,478,420	276,947,963	216,253,606	594,245,597	178,783,474	123,498,308	1,654,207,368
Block	Market-Making	552,479,837	547,492,475	721,401,931	2,126,195,917	767,071,838	932,944,760	5,647,586,758
	Matchmaking	713,415,421	1,050,824,045	437,370,556	1,944,616,931	991,895,809	714,432,496	5,852,555,258

Table 28: Total Profits of Trade Groups: Market-Making vs. Matchmaking

Trade Group	Trade Type	Dec 2016	Jan 2017	Dec 2017	Jan 2018	Dec 2018	Jan 2019	Total
Micro	Market-Making	35,433,000	39,116,500	32,898,000	44,404,000	31,883,000	33,012,000	216,746,500
	Matchmaking	1,159,000	2,180,000	1,074,000	1,300,000	1,104,000	921,000	7,738,000
Odd-lot	Market-Making	55,955,000	47,282,000	65,507,000	113,910,000	51,193,000	48,559,000	382,406,000
	Matchmaking	3,664,000	3,216,000	3,594,000	6,058,000	1,956,000	1,880,000	20,368,000

Table 29: Non-Outlier Volumes of Trade Groups: Market-Making vs. Matchmaking

Trade Group	Trade Type	Dec 2016	Jan 2017	Dec 2017	Jan 2018	Dec 2018	Jan 2019	Total
Micro	Market-Making	115,654,039	119,162,822	107,106,310	150,193,033	122,985,828	124,122,965	739,225,997
	Matchmaking	4,359,321	7,348,470	3,720,644	4,385,662	4,367,588	3,540,232	27,721,917
Odd-lot	Market-Making	287,401,587	234,086,971	307,905,686	594,777,084	262,302,117	240,434,901	1,927,908,346
	Matchmaking	19,953,087	17,042,656	19,421,677	33,956,924	10,461,671	11,610,832	112,446,847

Table 30: Non-Outlier Profits of Trade Groups: Market-Making vs. Matchmaking

Trade Group	Trade Type	Dec 2016	Jan 2017	Dec 2017	Jan 2018	Dec 2018	Jan 2019	Total
Micro	Market-Making	500,000	0	0	0	0	110,000	610,000
Odd-lot	Market-Making	96,594,000	78,532,000	59,889,000	61,705,000	66,802,000	68,355,000	431,877,000
	Matchmaking	13,740,000	11,221,000	7,965,000	6,097,000	4,019,000	4,375,000	47,417,000
Round-lot	Market-Making	125,891,000	129,631,000	127,856,000	189,396,000	133,998,000	133,911,000	840,683,000
	Matchmaking	72,321,000	74,705,000	52,702,000	118,696,000	36,401,000	21,530,000	376,355,000
Block	Market-Making	184,030,000	150,095,000	172,613,000	376,327,000	146,473,000	154,826,000	1,184,364,000
	Matchmaking	162,455,000	241,279,000	104,357,000	335,628,000	161,747,000	106,240,000	1,111,706,000

Table 31: Outlier Volumes of Trade Groups: Market-Making vs. Matchmaking

Trade Group	Trade Type	Dec 2016	Jan 2017	Dec 2017	Jan 2018	Dec 2018	Jan 2019	Total
Micro	Market-Making	486,306	0	0	0	0	75,221	561,527
Odd-lot	Market-Making	298,317,568	246,072,590	174,875,407	194,293,136	264,367,966	263,737,243	1,441,663,910
	Matchmaking	42,886,066	36,340,434	22,192,470	21,362,608	18,103,987	15,754,916	156,640,481
Round-lot	Market-Making	457,428,580	486,807,779	538,098,123	894,478,420	633,021,554	615,493,394	3,625,327,850
	Matchmaking	264,478,420	276,947,963	216,253,606	594,245,597	178,783,474	123,498,308	1,654,207,368
Block	Market-Making	552,479,837	547,492,475	721,401,931	2,126,195,917	767,071,838	932,944,760	5,647,586,758
	Matchmaking	713,415,421	1,050,824,045	437,370,556	1,944,616,931	991,895,809	714,432,496	5,852,554,258

Table 32: Outlier Profits of Trade Groups: Market-Making vs. Matchmaking

	(1) trade_ty~c_3	(2) trade_ty~c_3	(3) trade_ty~c_3	(4) trade_ty~c_3	(5) trade_ty~c_3	(6) trade_ty~c_3	(7) trade_ty~c_3	(8) trade_ty~c_3	(9) trade_ty~c_3
post	0.112***	0.0125*	0.114***	0.0767**	-0.00551	0.0803**	-0.0643*	-0.000840	-0.0797*
	(0.0377)	(0.00677)	(0.0423)	(0.0314)	(0.00645)	(0.0369)	(0.0377)	(0.00570)	(0.0435)
Price	-0.00146	-0.000316	0.0000163	-0.00598***	-0.000844*	-0.00522**	-0.00821***	-0.000965	-0.00772***
	(0.00243)	(0.000507)	(0.00272)	(0.00192)	(0.000438)	(0.00216)	(0.00246)	(0.000626)	(0.00275)
Yield	0.0451***	0.00590***	0.0537***	0.0124	0.00333*	0.0121	0.0132	0.00109	0.0151
	(0.00968)	(0.00191)	(0.0107)	(0.00783)	(0.00178)	(0.00947)	(0.00855)	(0.00207)	(0.00982)
Quantity	3.64e-08***	0.000000359**	2.81e-08**	3.27e-08**	0.000000400***	1.78e-08	4.44e-08***	0.000000217	3.93e-08***
	(1.26e-08)	(0.000000182)	(1.25e-08)	(1.32e-08)	(0.000000113)	(1.39e-08)	(1.39e-08)	(0.000000161)	(1.43e-08)
cntra_mp_id==A	-0.619***	-0.0177	-0.628***	-0.346***	-0.0220	-0.383***	-0.189***	-0.0361***	-0.215***
	(0.152)	(0.0334)	(0.135)	(0.0387)	(0.0245)	(0.0355)	(0.0521)	(0.00479)	(0.0540)
cntra_mp_id==C	0.0812	0.0107	0.0723	0.0184	-0.0184***	0.0324	0.0402	-0.00453	0.0473
	(0.0835)	(0.0149)	(0.0927)	(0.0733)	(0.00604)	(0.0866)	(0.0687)	(0.00871)	(0.0822)
Constant	0.209	0.0396	0.0906	0.738***	0.0967**	0.732***	0.895***	0.116*	0.875***
	(0.276)	(0.0559)	(0.306)	(0.216)	(0.0476)	(0.245)	(0.273)	(0.0683)	(0.306)
Observations	10827	8721	2106	12326	10133	2193	10183	8200	1983
Adjusted R-squared	0.110	0.006	0.105	0.084	0.010	0.062	0.184	0.004	0.161

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Table 33: Weighted DiD-Regressions Across All Observation Periods and Datasets

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	trade_ty~c_3	trade_ty~c_3	trade_ty~c_3	trade_ty~c_3	trade_ty~c_3	trade_ty~c_3	trade_ty~c_3	trade_ty~c_3	trade_ty~c_3
trade_type_numeric_3									
post	0.488***	0.247*	0.488**	0.323**	-0.0922	0.333*	-0.483**	-0.0281	-0.522**
	(0.174)	(0.133)	(0.190)	(0.162)	(0.152)	(0.175)	(0.215)	(0.172)	(0.227)
Price	-0.0158	-0.00626	-0.00609	-0.0348***	-0.0174*	-0.0259**	-0.0487***	-0.0214	-0.0420***
	(0.0113)	(0.00897)	(0.0124)	(0.00959)	(0.00903)	(0.0101)	(0.0122)	(0.0147)	(0.0130)
Yield	0.112**	0.120***	0.166***	0.0232	0.0871**	0.0336	0.0146	0.0322	0.0234
	(0.0525)	(0.0388)	(0.0569)	(0.0423)	(0.0418)	(0.0465)	(0.0467)	(0.0545)	(0.0494)
cntra_mp_id==A	-6.585***	-0.216	0	-3.286***	-0.452	-3.507***	-2.143**	0	-2.308**
	(0.925)	(0.820)	(.)	(0.980)	(0.845)	(1.026)	(1.059)	(.)	(1.061)
cntra_mp_id==C	0.529	0.197	0.457	0.136	-0.777***	0.172	0.293	-0.180	0.334
	(0.374)	(0.282)	(0.423)	(0.328)	(0.291)	(0.362)	(0.355)	(0.332)	(0.388)
Constant	0.371	-2.927***	-0.572	2.295**	-1.690	1.594	3.550***	-1.425	3.081**
	(1.307)	(1.025)	(1.426)	(1.124)	(1.047)	(1.182)	(1.359)	(1.661)	(1.439)
Observations	10827	8721	2084	12326	10133	2193	10183	8153	1983
Adjusted R-squared									

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Table 34: Weighted Logit-Regressions Across All Observation Periods and Datasets

	(1) trade_ty~c_3	(2) trade_ty~c_3	(3) trade_ty~c_3	(4) trade_ty~c_3	(5) trade_ty~c_3	(6) trade_ty~c_3	(7) trade_ty~c_3	(8) trade_ty~c_3	(9) trade_ty~c_3
post	0.0198***	0.0176***	0.0287	0.00669	-0.0103***	0.0728***	-0.000445	0.00103	-0.0176
	(0.00522)	(0.00467)	(0.0179)	(0.00472)	(0.00393)	(0.0190)	(0.00437)	(0.00395)	(0.0150)
Price	-0.000246	0.000891**	-0.000444	-0.00214***	-0.000275	-0.00310**	-0.00247***	-0.00104***	-0.00406***
	(0.000434)	(0.000369)	(0.00135)	(0.000357)	(0.000278)	(0.00121)	(0.000460)	(0.000383)	(0.00148)
Yield	0.0119***	0.00770***	0.0280***	0.00766***	0.00133	0.0226***	0.00301**	-0.000744	0.0144***
	(0.00144)	(0.00132)	(0.00477)	(0.00125)	(0.00104)	(0.00501)	(0.00139)	(0.00115)	(0.00488)
Quantity	0.000000124***	0.000000151	9.10e-08***	0.000000144***	0.000000233***	6.94e-08***	0.000000116***	0.000000129	8.82e-08***
	(1.50e-08)	(0.000000137)	(1.34e-08)	(1.26e-08)	(8.51e-08)	(1.12e-08)	(1.45e-08)	(0.000000117)	(1.36e-08)
cntra_mp_id==A	-0.124**	0.0275	-0.307***	-0.118***	0.00636	-0.283***	-0.0631***	-0.0333***	-0.108***
	(0.0522)	(0.0566)	(0.0633)	(0.0251)	(0.0321)	(0.0285)	(0.0141)	(0.00244)	(0.0299)
cntra_mp_id==C	0.00414	0.00618	0.0292	-0.0156**	-0.00917	0.000397	-0.00749	-0.00826	-0.0117
	(0.0113)	(0.0103)	(0.0472)	(0.00793)	(0.00653)	(0.0486)	(0.00688)	(0.00619)	(0.0296)
Constant	0.0356	-0.0832**	0.0913	0.237***	0.0604**	0.370***	0.266***	0.135***	0.411**
	(0.0472)	(0.0401)	(0.147)	(0.0387)	(0.0305)	(0.137)	(0.0500)	(0.0417)	(0.163)
Observations	10827	8721	2106	12326	10133	2193	10183	8200	1983
Adjusted R-squared	0.073	0.005	0.084	0.096	0.002	0.078	0.083	0.002	0.138

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Table 35: Unweighted DiD-Regressions Across All Observation Periods and Datasets

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	trade_ty~c_3	trade_ty~c_3	trade_ty~c_3	trade_ty~c_3	trade_ty~c_3	trade_ty~c_3	trade_ty~c_3	trade_ty~c_3	trade_ty~c_3
trade_type_numeric_3									
post	0.259***	0.369***	0.173	0.102	-0.282***	0.420***	-0.0334	0.0269	-0.190
	(0.0716)	(0.0983)	(0.108)	(0.0749)	(0.105)	(0.109)	(0.0917)	(0.127)	(0.137)
Quantity	0.000000945***	0.00000306	0.000000542***	0.00000103***	0.00000572***	0.000000336***	0.000000924***	0.00000403	0.000000525***
	(0.000000113)	(0.00000260)	(8.12e-08)	(0.000000104)	(0.00000187)	(5.61e-08)	(0.000000151)	(0.00000336)	(9.78e-08)
Price	0.000203	0.0186***	0.00166	-0.0225***	-0.00666	-0.0134**	-0.0306***	-0.0282***	-0.0216**
	(0.00515)	(0.00698)	(0.00749)	(0.00455)	(0.00733)	(0.00621)	(0.00617)	(0.00991)	(0.00914)
Yield	0.161***	0.160***	0.180***	0.104***	0.0338	0.127***	0.0586**	-0.0246	0.129***
	(0.0198)	(0.0269)	(0.0305)	(0.0192)	(0.0281)	(0.0283)	(0.0230)	(0.0351)	(0.0337)
cntra_mp_id==A	-2.163	0.460	0	-2.254**	0.159	-3.157***	-2.057*	0	-1.873*
	(1.957)	(0.744)	(.)	(1.017)	(0.728)	(1.033)	(1.148)	(.)	(1.057)
cntra_mp_id==C	-0.00112	0.135	0.0848	-0.368**	-0.309	0.00299	-0.276	-0.309	-0.158
	(0.166)	(0.214)	(0.266)	(0.181)	(0.247)	(0.258)	(0.197)	(0.263)	(0.292)
Constant	-3.423***	-5.776***	-2.594***	-1.009*	-2.705***	-0.866	-0.457	-0.635	-0.873
	(0.578)	(0.782)	(0.840)	(0.518)	(0.818)	(0.721)	(0.696)	(1.107)	(1.028)
Observations	10827	8721	2084	12326	10133	2193	10183	8153	1983
Adjusted R-squared									

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Table 36: Unweighted Logit-Regressions Across All Observation Periods and Datasets