Shadow Discounts*

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Abstract

Centralized trading platforms should improve competition in OTC markets. Using transaction records from the U.S. corporate bond market and exploiting variation within client-dealer relationships, we find no evidence that clients receive better secondary-market trading terms after adopting a platform. To reconcile this puzzling finding, we present a model in which relationship dealers operate in both primary and secondary markets. A central insight, for which we find strong empirical support, is that dealers respond to clients' improved outside options not by changing secondary-market terms, but by granting larger primary-market allocations. Guided by the model, we estimate that platform adoption is worth 77% of clients' pre-adoption profits from primary-market allocations. Overall, the effects of platforms in OTC markets are more complex than previously thought.

JEL-Classification: G10, G12, G22
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1 Introduction

Client-dealer relationships play a central role in over-the-counter (OTC) markets. By repeatedly trading with the same dealers, clients reduce search frictions and gain access to liquidity (Allen and Wittwer, 2023). At the same time, these relationships may give dealers market power and allow them to earn relationship-specific rents (Li and Schurhoff, 2019; Hendershott et al., 2020). Centralized trading platforms can reshape these relationships. By making it easier for clients to access competing dealers, platforms reduce search frictions and intensify competition. The conventional view therefore is that stronger competition improves clients' secondary-market trading terms by weakening dealers' market power.

We propose an alternative view. Dealers interact with clients in both the primary and secondary markets and can therefore adjust client relationships across markets. When a relationship client adopts a centralized trading platform, competition increases in the secondary market. Rather than competing through better secondary-market trading terms, dealers preserve the relationship by granting larger primary-market allocations.

We test this mechanism using insurer clients in the corporate bond market and exploit within client-dealer variation around platform adoption. We develop a high-frequency identification strategy that pinpoints the timing of adoption at the individual-client level. Platform adoption leaves secondary-market relationships largely unchanged. Clients continue to trade the same assets and volumes with their relationship dealers, at the same costs and with the same performance. In contrast, relationship dealers increase clients' primary-market allocations by 29% (approximately $1 million per offering). Because new issues are underpriced, these larger allocations translate into higher profits for adopting clients. We find no evidence that issue size or underpricing changes around adoption. Instead, dealers reallocate primary-market allocations toward clients whose outside options have improved.

Section 2 describes our data, which contain the universe of corporate-bond transaction records by U.S. insurers from 2006 to 2019, filed with the National Association of Insurance Commissioners (NAIC). We observe the counterparties to each transaction, which we exploit to follow the same

client-dealer relationships over time. Our sample contains 196 dealers and 367 insurer clients that manage their own portfolios, spanning 50,000 secondary-market transactions and 14,000 primary-market allocations. We study the adoption of MarketAxess, the largest corporate-bond trading platform in the U.S.

Section 3 identifies each client's platform adoption using her first trade through Open Trading (OT), an anonymous all-to-all trading protocol. Once a client adopts the platform, requests are by default sent simultaneously to dealers and to the OT segment. We therefore hypothesize that clients experiment with unusually many requests upon platform adoption and are likely to execute their first OT trade on that day. Consistent with this hypothesis, the volume, the number of trades, and the number of dealer counterparties–especially new dealer connections–increase sharply on the first OT day, with no pre-trends or post-trends over the surrounding two years. Placebo tests show that this spike is unique to the first OT trade. We therefore use a client's first OT trade as a proxy for her platform adoption date.

Section 4 examines the impact of platform adoption on clients' secondary-market relationships. We compare trading activity within each client-dealer pair in the one-year window before and after the client's adoption date. Clients' trade volume and frequency with their relationship dealers remain unchanged, and there is no improvement in price discrimination. They perform similarly on their trades over any time horizon, are no more likely to split trades across dealers, and do not shift trading toward less liquid bonds or a broader set of assets. Granular fixed effects rule out asset- and time-specific confounders. In sum, there is no evidence that platform adoption changes secondary-market client-dealer relationships, despite the sharp increase in new dealer connections upon adoption.

Section 5 develops a simple model of a client-dealer relationship that rationalizes why clients' secondary-market outcomes can remain unchanged following an increase in competition. The dealer sets the client's secondary-market spread and may allocate part of an underpriced primary-market offering to the client. The dealer maximizes profits subject to the client receiving at least her outside option. In equilibrium, the dealer chooses the spread that maximizes the joint client-dealer

surplus. Platform adoption is modeled as an exogenous increase in the client's outside option.

We derive two main results. First, the dealer responds to platform adoption exclusively by increasing the client's primary-market allocation. The client's secondary-market spread, trade quantity, and payoff remain unchanged. Second, clients with greater bargaining power experience a *smaller* increase in their primary-market allocation following platform adoption.

Our key insight is that the primary allocation is a lump-sum transfer from the dealer to the client. Enlarging this lump-sum transfer does not distort client demand, leaving the joint surplus unchanged. The spread, by contrast, is the client's marginal cost. Discounting the spread would therefore distort client demand and shrink the joint surplus, making it more costly to the dealer than enlarging the allocation. We call the enlarged allocation a "shadow discount" that substitutes for a discount in the secondary market. The shadow discount is larger if the client has little bargaining power, because she is pinned closer to her outside option. The increase in the outside option therefore needs to be fully compensated by a larger shadow discount. A high bargaining-power client already extracts far more of the joint surplus than her outside option, leading to a smaller shadow discount upon an increase in this option.

Section 6 turns to primary-market outcomes and tests the model's predictions. Again exploiting within client-dealer variation, we find that adopting clients receive larger allocations from their relationship dealers. The total bond issue, the dealer's total allocation across all clients, and underpricing all remain unchanged, suggesting that our results are not driven by other changes correlated with a client's adoption. A client's adoption also does not correlate with greater flipping activity or access to new assets in the primary market.

To test for heterogeneity in bargaining power, we exploit a revealed-preference implication of the model: pre-adoption allocations are lower (higher) when a client has less (more) bargaining power. We therefore compute, for each client-dealer relationship, the share of the client's total pre-adoption primary-market allocations received from that dealer. Consistent with the model's prediction, high-share clients' allocations increase by 18% upon adoption, compared with 52% for low-share clients. We provide further robustness tests supporting this mechanism.

In the final part of the paper, we estimate the value of platform adoption. Guided by the model, we define $Profit$ as the product of a client's primary-market allocation and underpricing. The model implies that the adoption-induced change in $Profit$ measures the increase in the client's outside option. Our estimates imply that, for the average client, platform adoption is worth 77% of pre-adoption profits from primary-market allocations. This magnitude suggests that platform adoption generates economically meaningful benefits.

Recent theoretical work (see, e.g., Kargar et al., 2026) on the multifaceted nature of OTC markets calls for micro-data to understand the role of trading platforms. We provide such micro-level evidence and uncover a novel mechanism: primary-market allocations sustain client-dealer relationships despite stronger platform competition. More broadly, our findings suggest that the effects of trading platforms cannot be understood by studying individual markets in isolation when intermediaries operate across multiple markets.

Literature. We contribute to the recent and growing body of research analyzing centralized trading platforms in corporate bond markets. Theoretically, the literature has explored how electronic and OTC markets can coexist (Bolton, Santos, and Scheinkman, 2016; Allen and Wittwer, 2023; Lee and Wang, 2025). On the empirical side, multiple studies have exploited data from MarketAxess to examine the impact of electronic trading on various market dimensions, including liquidity (O'Hara and Zhou, 2021; Hendershott, Livdan, and Schurhoff, 2025), dealer quoting behavior (Hendershott et al., 2025), and customer sequential search (Kargar et al., 2025). In these existing studies, customers' identities are typically anonymized. Our paper differs from the existing literature by leveraging insurance companies' individual transaction records, which allow us to (i) observe customer identities and thereby identify effects within trading relationships, and (ii) track clients' trading activity before and after platform adoption.

We make three contributions to this literature. First, we provide the first client-level evidence on the effects of platform adoption in OTC markets. Second, we show that platform adoption does not change secondary-market client-dealer relationships. Third, we identify primary-market allo-

cations as the mechanism through which client-dealer relationships are sustained despite stronger competition.

We also contribute to the literature on client-dealer relationships in the corporate bond market. While a large body of work documents the structure of trading networks (Hendershott et al., 2020; Li and Schurhoff, 2019; Grotteria et al., 2026) and their economic benefits (Di Maggio, Kermani, and Song, 2017; Kondor and Pintér, 2022; Comerton-Forde et al., 2025), much less is known about how these relationships adjust when competition increases. We show that stronger competition in the secondary market does not weaken client-dealer relationships because dealers can make transfers across markets.

2 Data

Our primary data source is eMAXX, which provides daily transaction records for U.S. insurance companies through the 'BROKTRAN' file. These data are compiled from Schedule D filings submitted to the National Association of Insurance Commissioners (NAIC). Insurance companies are required to report both their daily transactions and portfolio holdings to the NAIC. Importantly, the individual transaction records identify the counterparty to each record; either a dealer or a trading platform. Our sample covers the period from 2006 Q1 to 2019 Q4.

We conduct our analysis at the fund level and include all insurance sectors. (i.e. life, health, property & casualty, reinsurance, other). We exclude insurers that delegate portfolio management to an asset management company. These insurers do not make their own trading decisions (e.g., regarding technology or execution), and their trading networks are not uniquely attributable to them as they belong to the asset manager (see Ozdagli and Ryfe, 2025). We manually identify those insurers by the 'parent name' in the transaction records, and we provide the full list of asset managers and the number of insurers they manage in Table IA.I in the Internet Appendix.

We further collect information on bond characteristics from Mergent FISD and match it with the trading data using the CUSIP identifier. We exclude the following bonds: yankee, canadian,

foreign currency, sinking fund, exchangeable, convertible, and private placements. We only use bonds for which we can match the CUSIP identifier to a GVKEY in Compustat, and we exclude bonds with missing offering date, maturity, offering amount, and coupon.

We focus on MarketAxess, the largest electronic trading platform, which accounts for approximately 85% of dealer-to-customer institutional electronic trading in U.S. corporate bonds (see O'Hara and Zhou, 2021). We manually identify MarketAxess among the counterparties in the data, where it appears as either '*Market Axess Inc*' or '*MarketAxess Corporation*.' Any transaction for which MarketAxess is reported as the counterparty is executed through Open Trading (OT)–an all-to-all trading protocol in which trading is anonymous and MarketAxess acts as the reporting party facilitating the trade (see Section 3 for more details).

TABLE 1 ABOUT HERE

Our sample includes 367 clients and 196 dealers. Table 1 reports summary statistics across different levels of aggregation. Panel A reports summary statistics for the secondary market at the client × dealer × trading day level (i.e., excluding the OT segment). The average transaction volume is close to $2.7 million, with a standard deviation of $6.1 million, indicating substantial variation. The average number of trades is 1.3 (standard deviation of 1.8) and, on average, 1.2 assets are traded (standard deviation of 1.5).

Panel B, which also focuses on the secondary market, presents statistics at the individual transaction record. We report summary statistics on price discrimination, using the best available transaction price as the benchmark (see equation (3) for the computation), which is 36 basis points, on average, with a standard deviation of 62 basis points.

Panel C reports statistics for allocations in the primary market. Average allocation quantities are close to $5.1 million, with a standard deviation of $10.3 million. Profit from a primary-market allocation (see equation (19) for the computation) averages approximately $13,500, with a standard deviation of $45,600.

In the subsequent sections, we exploit the data to examine how platform adoption is associated with changes in trading within client-dealer relationships.

3 Identifying platform adoption

In this section, we describe our strategy for identifying when clients adopt the platform. Although adoption decisions are inherently unobservable, we exploit a high-frequency approach combined with institutional features of the market to infer the timing of platform adoption.

The standard protocol used by electronic trading platforms is the request-for-quote (RFQ) mechanism. After adopting the platform, a client can submit RFQs to multiple dealers and execute the trade with the best quote. Under the RFQ protocol, both the client and the executing dealer observe each other's identities, but an individual dealer does not know how many other dealers were contacted. As a result, our transaction data record only the executed transaction and its counterparty, without indicating whether the trade originated from an RFQ process.

We can, however, exploit an institutional feature of both the data and the platform technology. Specifically, we identify the first day on which a client reports MarketAxess as a counterparty. Although MarketAxess is not a traditional dealer, it is recorded as the counterparty whenever a trade is executed through Open Trading (OT), the anonymous all-to-all trading protocol introduced by MarketAxess in 2012. OT is automatically enabled; therefore, when a client submits an RFQ, the request is directed not only to connected dealers but also to participants in the OT network. We therefore expect newly adopting clients to experiment with the platform by sending unusually many requests, making an OT trade particularly likely on the adoption day. Hence, the first OT trade provides a plausible proxy for platform adoption, an assumption that we validate below.

To validate the assumption that the first day on which MarketAxess is reported as a counterparty corresponds to the platform adoption date, we employ a high-frequency approach to detect abnormal trading activity. Specifically, we restrict the analysis to the bilateral market (i.e., excluding OT trades) and estimate the following regression:[1]

$$Y_{c,k_c+s} = \sum_s \beta_s \times \mathbb{I}_{c,k_c+s} + \alpha_c + \epsilon_{c,k_c+s}, \tag{1}$$

[1] As documented by Hendershott, Livdan, and Schurhoff (2025), OT volume remains relatively small, accounting for roughly 2–3% of total trading volume. Our sample confirms this pattern: around 2% of trading volume is executed through OT in the year following adoption.

where Y_{c,k_c+s} measures a trading outcome for client c on day $k_c + s$, relative to the client's first OT trade date k_c (i.e. event date), $\mathbb{I}_{c,k_c+s}$ is an indicator equal to one on day $k_c + s$, and α_c denotes client fixed effects. We consider the window $s \in [-365, 365]$ days around k_c and use $s = -1$ as the omitted reference day. Standard errors are clustered at the client level.

FIGURE 1 ABOUT HERE

The coefficient β_s captures the day-to-day dynamics of trading activity within a client. Panel A of Figure 1 reports the results for trading volume. Trading volume exhibits a sharp and statistically significant increase on the first OT trading day, with no comparable effect on any other day within the two-year window. Panels B and C show similar patterns for the number of trades and the number of dealers involved, respectively, with both significantly surging on the first OT day. In other words, trading activity in the bilateral segment exhibits an abnormal spike on the first OT trading day, which is consistent with this date marking the onset of platform adoption.

While the increase in trading activity establishes that the first OT day marks a significant change in client behavior, it does not by itself distinguish platform adoption from other shocks to trading demand. We therefore examine the formation of new dealer relationships, a distinctive prediction of platform adoption; that is, centralized trading platforms are designed to facilitate the discovery and formation of new connections.[2] Consequently, if the first OT trade date indeed corresponds to the onset of platform usage, one would expect a surge in newly established dealer connections on that day.

Panel D confirms this prediction. The number of new trading connections exhibits a sharp spike on the first OT trading day, but not on any other day within the two-year event window. This finding provides strong additional evidence that our identification strategy successfully captures the onset of platform usage, as the nature of the change matches what platform adoption should produce: new dealer connections.

Moreover, Panels A to D exhibit no evidence of pre-trends, providing additional support for our identifying assumption and suggesting that high-frequency measurement of platform adoption

[2]Platforms may even suggest potential dealer connections to users.

alleviates concerns that arise when adoption is measured at lower frequencies, such as annually or quarterly.

We conduct a placebo test to assess whether our procedure accurately identifies the adoption date. Specifically, we shift the estimated adoption date two years earlier and re-estimate equation (1) over the window spanning three to one years before adoption. If the estimated adoption date merely reflected random fluctuations in trading activity or relationship formation, similar spikes should emerge elsewhere within the placebo window.

However, Figure 2 shows no comparable surges in trading activity or the formation of new dealer relationships elsewhere in the placebo window. Thus, the first OT trading day is unique within the four-year window, providing strong evidence that our procedure accurately identifies the platform adoption date.

FIGURE 2 ABOUT HERE

Finally, we provide descriptive evidence that the estimated adoption dates align with gradual diffusion of the platform. Figure IA.1 in the Internet Appendix plots the number of adoption events over time. Most adoption events occur after 2014 and peak in 2019. This gradual diffusion is reassuring, given that OT was introduced only in 2012. If a substantial share of clients had already been active on the platform before OT was introduced, one would expect many first OT trades to occur shortly after 2012. Instead, adoption events are spread over subsequent years, reinforcing the interpretation that the first reported OT trade coincides with actual platform adoption.

4 Testing for secondary-market effects of platform adoption

Having identified the onset of a client's platform usage, we next examine whether platform adoption changes existing client-dealer relationships. Standard economic intuition suggests that the ability to request quotes from multiple dealers should intensify competition, leading clients to rely less on existing relationships and obtain more favorable trading terms.

To study how platform adoption affects trading relationships, we exploit the granularity of our data and analyze variation within client × dealer pairs. Accordingly, we focus on the bilateral segment of the secondary market (SM) and exclude OT trades. We then examine whether trading outcomes within a given client-dealer relationship change following the client's adoption of the platform.

We find no evidence that platform adoption alters existing client-dealer relationships, despite the sharp increase in new dealer connections upon adoption. Across all trading outcomes we examine, the estimated effects are economically small and statistically insignificant. This finding presents a puzzle for standard theories of dealer competition, which predict that easier access to multiple dealers should weaken existing bilateral relationships and improve trading terms.

4.1 SM: no change in trading volume

We start to aggregate the data at the client × dealer × trading-day level over the one-year window before and after a client's adoption date. We then estimate the following regression:

$$Y_{c,d,t_c} = \beta \times PostAdoption_{c,t_c} + \alpha_{c\times d} + \alpha_{yq} + \epsilon_{c,d,t_c}, \tag{2}$$

where c indexes clients, d dealers, and t_c a client's trading days. $PostAdoption_{c,t_c}$ is an indicator variable that equals one after client c adopts the platform and zero beforehand. The key fixed effect is $\alpha_{c\times d}$, implying that the coefficient β captures the effect of platform adoption on the trading outcome Y_{c,d,t_c} within a given client-dealer relationship. We additionally include year-quarter fixed effects and cluster standard errors at the client level.

We report the results using trading volume as the dependent variable, Y_{c,d,t_c}, in Table 2. In column (1), we estimate a statistically insignificant β coefficient of \$113,000 (approximately 4% of the sample mean; $|t| < 0.7$), indicating that trading volume within client-dealer relationships remains unaffected by a client's platform adoption. In column (2), we exclude the adoption day from the sample and find an even smaller β coefficient of \$75,000 ($|t| < 0.5$), providing further

evidence that platform adoption does not change trading volume within client-dealer relationships.

TABLE 2 ABOUT HERE

In Table IA.II of the Internet Appendix, we re-estimate equation (2) using a balanced sample spanning one year before and one year after the adoption day, excluding the adoption day itself. We use an indicator as the dependent variable: if client c trades with dealer d on day t, the indicator equals one; otherwise, it equals zero. This specification additionally captures the extensive margin, namely whether the likelihood of trading on any given day changes. The estimated β coefficient is statistically insignificant ($|t| < 1$) and is even negative, indicating that, if anything, the probability of trading declines. Taken together, these results indicate that platform adoption does not alter trading activity within existing client-dealer relationships, suggesting that the competitive effects of platform adoption play little role in the bilateral secondary market.

4.2 SM: no change in prices

We next turn to the individual transaction records and examine whether platform adoption is associated with changes execution prices. We first focus on price discrimination and then turn to performance effects.

Price discrimination. There is substantial evidence that search frictions affect transaction prices (see, e.g., Friewald and Nagler, 2019), and trading platforms are designed to reduce these frictions and thereby foster competition. Thus, if the primary effect of platform adoption is to reduce search frictions and intensify dealer competition, one would expect price discrimination in the bilateral market to decline following adoption. To test this prediction, we construct the following transaction-record measure of price discrimination (see, e.g., O'Hara, Wang, and Zhou, 2018; Pinter, Wang, and Zou, 2024):

$$PD_{c,a,d,t_c} = \left[\ln(P_{c,d,a,t_c}) - \ln(P^*_{a,t_c})\right] \times \mathbf{1}^{B,S}_{c,d,a,t_c}, \tag{3}$$

where P_{c,d,a,t_c} denotes the transaction price obtained by client c from dealer d for asset a on client's trading day t_c, P^*_{a,t_c} is the corresponding benchmark price, and $\mathbf{1}^{B,S}_{c,d,a,t_c}$ is an indicator equal to one for buy transactions (B) and minus one for sell transactions (S).

To assess robustness, we use three alternative benchmark prices, all constructed from data provided by the Trade Reporting and Compliance Engine (TRACE). The first benchmark is the best observed transaction price for asset a across trades in the same direction during the three days preceding t_c. The second benchmark is the volume-weighted average transaction price of asset a across all trades during the three days preceding t_c. Finally, the third benchmark is based on the volume-weighted average interdealer transaction price of asset a during the three days preceding t_c. We again focus over the one-year window before and after a client's adoption date and run the following regression:

$$Y_{c,d,a,t_c} = \beta \times PostAdoption_{c,t_c} + \alpha_{c\times d} + \alpha_{a\times yq} + \epsilon_{c,d,a,t_c}, \tag{4}$$

where Y_{c,d,a,t_c} denotes the outcome associated with a transaction record involving client c, dealer d, asset a, and client trading day t_c. As before, the indicator variable $PostAdoption_{c,t_c}$ equals one after client c adopts the platform and zero beforehand. The key fixed effect is $\alpha_{c\times d}$, implying that the coefficient β captures the effect of platform adoption on transaction-record price discrimination within a given client-dealer relationship. We additionally include asset × year-quarter $\alpha_{a\times yq}$ fixed effects, and cluster standard errors at the client level.

TABLE 3 ABOUT HERE

The results for price discrimination, PD_{c,d,a,t_c}, are reported in Table 3. Column (1) uses the best observed transaction price as the benchmark, column (2) the volume-weighted transaction price, and column (3) the volume-weighted interdealer transaction price. Across all specifications, the estimated β coefficients are statistically insignificant ($|t| < 0.5$); one (interdealer) even has the opposite sign. These results indicate that clients do not obtain better execution prices from their relationship dealers following platform adoption. In column (4), we use individual transaction size

as the dependent variable and again find no significant effect of platform adoption, as the estimated β coefficient is statistically insignificant ($|t| < 0.4$). Hence, the insignificant effect on execution prices is also not driven by changes in transaction size, such as a reduction in size-related price penalties (e.g., Pinter, Wang, and Zou, 2024).

In Table IA.III in the Internet Appendix, we re-estimate the specifications after excluding the adoption day from the sample. The estimated effects become even smaller and remain statistically insignificant for all three benchmark prices ($|t| < 0.4$), with one estimate having again the opposite sign. Similarly, we find no effects for transaction size.

Performance. Another possibility is that trading platforms facilitate the splitting of trading volume across dealers. This may allow clients to exploit potential informational advantages. To investigate this mechanism, we examine whether clients become more likely to split trades in the same asset across multiple dealers following platform adoption. Specifically, we estimate equation (4), using as the dependent variable an indicator equal to one if client c's trade with dealer d in asset a on trading day t_c is split across at least one additional dealer.

We report the results in column (1) of Table IA.IV in the Internet Appendix. The estimated β coefficient is positive but not statistically significant ($|t| < 1.6$), although its sign is consistent with a modest increase in trade splitting across dealers following platform adoption.

We next examine whether platform adoption improves clients' trading performance by enabling more effective trade timing or the exploitation of informational advantages. Specifically, following the methodology of Kondor and Pintér (2022), we define the following transaction-record performance measure:

$$Performance_{c,d,a,t_c+T} = \left[\ln(P_{a,t_c+T}) - \ln(P_{c,d,a,t_c})\right] \times \mathbf{1}^{B,S}_{c,d,a,t_c}, \tag{5}$$

where P_{a,t_c+T} denotes the volume-weighted average TRACE transaction price of asset a measured T days after trading day t_c, and $\mathbf{1}^{B,S}_{c,d,a,t_c}$ is the buy-sell side indicator (see equation (3)).

We then estimate equation (4) using $Performance_{c,d,a,t_c+T}$ as the dependent variable for

different horizons T. The results are reported in Table IA.IV in the Internet Appendix in columns (2)–(4), corresponding to horizons $T \in [1, 10]$, $T \in [11, 20]$, and $T \in [21, 30]$, respectively. The estimated β coefficients are statistically insignificant and have the wrong (negative) sign across all specifications, indicating that platform adoption does not improve clients' trading performance.

4.3 SM: no change in asset access

It is possible that, rather than competing on trading volume or execution prices following platform adoption, dealers compete by providing clients access to assets they had not previously traded. To examine this conjecture, we re-estimate the transaction-record specification in equation (4) with year-quarter fixed effects, α_{yq}, rather than asset × year-quarter fixed effects.

We first test whether post-adoption transactions are more likely to involve assets that the client has not previously traded. Specifically, we define the dependent variable Y_{c,d,a,t_c} as an indicator equal to one if client c trades with dealer d asset a on trading day t_c, and the asset has not been traded by the client during the preceding three or five years.

TABLE 4 ABOUT HERE

Columns (1) and (2) of Table 4 report the results. The estimated coefficients are statistically insignificant ($|t| < 1.1$) and even have the wrong sign (negative). Hence, following platform adoption, clients are no more likely to trade previously untraded assets with the same dealer, providing no evidence that relationship dealers respond by expanding the set of securities they trade with their clients.

We examine two additional dimensions of asset characteristics. First, we test whether clients become more likely to trade illiquid assets with the same dealer following platform adoption. To do so, we compute asset turnover during the quarter preceding the transaction and classify an asset as illiquid if its turnover falls below the median. The results are reported in column (3) of Table 4, where the estimated β coefficient is again statistically insignificant.

Second, we examine whether clients become more likely to trade high-yield assets following adoption. The results in column (4) show no evidence of such an effect, as the estimated β coefficient remains statistically insignificant.

Overall, the results so far show that platform adoption is not associated with changes in client-dealer relationships. Following adoption, clients continue to trade similar volumes with relationship dealers, at comparable prices, and in the same types of assets. This is puzzling because the conventional view is that trading platforms foster competition among dealers, which should weaken bilateral relationships and improve clients' trading terms. In the next section, we develop a simple theoretical framework featuring a dealer that is vertically integrated across the primary and secondary markets. The model shows how platform adoption can leave clients' outcomes in the secondary market unchanged while affecting outcomes in the primary market. We then test the model's predictions and find empirical support for them.

5 A model of platform adoption in client-dealer relationships

This section develops a simple theoretical framework to explain how platform adoption affects client-dealer relationships. The key insight is straightforward: because a primary-market allocation acts as a transfer between the dealer and the client, a dealer can satisfy a client's higher outside option by adjusting allocations rather than secondary-market trading terms. We formalize this intuition in a model of a vertically integrated dealer who chooses a secondary-market spread and a primary-market allocation to maximize profits subject to the client's participation constraint. We first describe the environment and characterize the equilibrium. We then discuss the intuition behind the results and present a more general version of the framework in the Internet Appendix.

5.1 Environment

We consider a client-dealer relationship that spans both the primary and secondary markets. This is a key feature of the institutional environment, as dealers in the corporate bond market typically

operate in both the primary and secondary markets (see, e.g., Nagler and Ottonello, 2022). In the primary market, dealers act as underwriters and allocate new offerings to investors. In the secondary market, they intermediate trades and provide liquidity.

Let $p \in \{0, 1\}$ be the indicator variable that equals one after the client adopts the platform and zero before adoption. The client has outside option $\underline{U}_p$ that increases after adoption

$$\underline{U}_1 > \underline{U}_0.$$

In the secondary market, the dealer chooses a spread $s > 0$ for the client. After observing s, the client chooses demand d to maximize secondary-market utility $U(s, d)$. Let

$$D(s) \in \arg\max_{d \geq 0} U(s, d)$$

denote the client's secondary-market demand. The assumptions stated below ensure that demand is strictly positive and decreasing in the spread, so that $D(s) > 0$ and $D'(s) < 0$.

In the primary market, the dealer chooses an allocation a to the client. Because the dealer forgoes the spread s on each unit allocated, the allocation generates a transfer of sa from the dealer to the client. The client's total relationship utility is

$$\mathcal{U}_p(s, a) = sa + U(s, D(s)). \tag{6}$$

The dealer's profit is

$$\Pi(s, a) = sD(s) - sa. \tag{7}$$

Assumptions. A standard set of sufficient conditions for existence and uniqueness is as follows. Assume that U is twice continuously differentiable on $(0, \infty) \times [0, \infty)$. For every spread $s > 0$, suppose that for all $d \geq 0$ we have that $U_d(s, 0) > 0$, $\lim_{d \to \infty} U_d(s, d) < 0$, and $U_{dd}(s, d) < 0$.

These conditions imply that the client's secondary-market demand is uniquely determined and

interior. The optimal demand $D(s)$ is characterized by

$$U_d(s, D(s)) = 0.$$

In addition, assume that

$$U_{sd}(s, d) < 0$$

for all relevant (s, d). The implicit function theorem to the client's first-order condition yields

$$D'(s) = -\frac{U_{sd}(s, D(s))}{U_{dd}(s, D(s))} < 0, \tag{8}$$

so that demand is decreasing in the spread.

To establish uniqueness of the dealer's optimal spread, define

$$G(s) \equiv D(s) + U_s(s, D(s)) - s\frac{U_{sd}(s, D(s))}{U_{dd}(s, D(s))}. \tag{9}$$

Assume that $G(s)$ is strictly decreasing in s and satisfies the boundary conditions

$$\lim_{s \downarrow 0} G(s) > 0, \qquad \lim_{s \to \infty} G(s) < 0.$$

Then, there exists a unique interior solution $s^* > 0$ satisfying $G(s) = 0$. Since $D(s)$ is uniquely determined for every s, the equilibrium pair $(s^*, D(s^*))$ is also unique. These conditions are sufficient, but not necessary, for uniqueness. Importantly, all uniqueness restrictions are imposed on the secondary-market utility function U and the demand function it induces. The comparative statics with respect to platform adoption derived below do not rely on uniqueness.

5.2 The dealer's problem

For each adoption state p, the dealer chooses (s, a) to solve

$$\max_{s>0,a} \quad sD(s) - sa \tag{10}$$

subject to

$$sa + U(s, D(s)) = \underline{U}_p. \tag{11}$$

The participation constraint requires the dealer to match the client's outside option.

We next characterize the dealer's optimal spread and allocation, (s^*, a^*). The participation constraint implies that, for any spread s,

$$a_p(s) = \frac{\underline{U}_p - U(s, D(s))}{s}. \tag{12}$$

Substituting (12) into the dealer's objective yields

$$\begin{aligned} \Pi(s, a_p(s)) &= sD(s) - s\left[\frac{\underline{U}_p - U(s, D(s))}{s}\right] \\ &= sD(s) + U(s, D(s)) - \underline{U}_p. \end{aligned} \tag{13}$$

Hence, the dealer chooses the spread from the reduced-form problem

$$s^* \in \arg\max_{s>0} \{sD(s) + U(s, D(s))\}. \tag{14}$$

The outside option $\underline{U}_p$ enters the objective as an additive constant and therefore does not affect the optimal spread.

For an interior solution, any optimal spread s^* satisfies

$$D(s^*) + s^*D'(s^*) + U_s(s^*, D(s^*)) + U_d(s^*, D(s^*))D'(s^*) = 0. \tag{15}$$

Because the client's demand is interior, $D(s)$ satisfies

$$U_d(s, D(s)) = 0.$$

Applying this condition to (15) yields

$$D(s^*) + s^* D'(s^*) + U_s(s^*, D(s^*)) = 0. \tag{16}$$

Using (8), this first-order condition is equivalent to $G(s^*) = 0$.

Given the optimal spread s^*, the dealer chooses the primary-market allocation in adoption state p to satisfy the participation constraint:

$$a_p^* = \frac{\underline{U}_p - U(s^*, D(s^*))}{s^*}. \tag{17}$$

Proposition 1. *Platform adoption does not affect the dealer's optimal spread correspondence. For any selected optimal spread $s^* > 0$, the optimal allocation is higher after adoption, i.e., $a_1^* > a_0^*$.*

Proof. The dealer chooses the spread by solving equation (14), which does not depend on the adoption state p. Therefore, platform adoption does not affect the set of optimal spreads.

For any selected optimal spread $s^* > 0$, equation (17) implies that

$$a_1^* - a_0^* = \frac{\underline{U}_1 - U(s^*, D(s^*))}{s^*} - \frac{\underline{U}_0 - U(s^*, D(s^*))}{s^*} = \frac{\underline{U}_1 - \underline{U}_0}{s^*}.$$

Since $\underline{U}_1 > \underline{U}_0$ and $s^* > 0$, it follows that $a_1^* - a_0^* > 0$. Hence, platform adoption increases the dealer's optimal primary-market allocation. □

Proposition 1 emphasizes a simple separation result. When platform adoption increases the client's outside option, it does not affect the surplus generated within the client–dealer relationship. As a result, adoption does not change the dealer's optimal spread. Instead, the dealer compensates the client through a transfer by adjusting the primary-market allocation to satisfy the client's

higher participation constraint, thereby generating a 'shadow discount.' The entire effect of platform adoption is therefore absorbed through larger primary-market allocations rather than lower secondary-market spreads.

5.3 Extension: bargaining power

The baseline model gives the dealer full bargaining power. We now consider a more general environment in which the dealer and client bargain over the terms of the relationship. Let $\theta \in [0, 1]$ denote the client's bargaining weight and suppose the dealer and client divide surplus according to the generalized Nash bargaining solution. Because secondary-market trading is not contractible, any credible agreement must implement the client's optimal demand $D(s)$. The bargaining problem therefore concerns the spread s and the primary-market allocation a. Let

$$W \equiv \max_{s>0} \{sD(s) + U(s, D(s))\}$$

denote the maximum joint surplus generated by the relationship. Since the allocation is a transfer between the dealer and the client, it does not affect joint surplus. Consequently, any efficient bargaining outcome selects a spread that maximizes joint surplus and therefore coincides with the optimal spread in the baseline model. Assume that $W > \underline{U}_1$, so that a mutually beneficial relationship exists both before and after adoption.

Proposition 2. *For any bargaining weight $\theta \in [0, 1]$, the generalized Nash bargaining outcome selects a spread from the set of optimal spreads characterized in Proposition 1. The client's equilibrium utility is $\underline{U}_p + \theta \left(W - \underline{U}_p\right)$. For any selected optimal spread $s^* > 0$, the corresponding allocation is*

$$a_p^\theta = \frac{\underline{U}_p + \theta \left(W - \underline{U}_p\right) - U(s^*, D(s^*))}{s^*}.$$

Moreover, for every $\theta \in [0, 1)$ *and any common selected optimal spread* $s^* > 0$*,*

$$a_1^\theta - a_0^\theta = \frac{(1-\theta)(\underline{U}_1 - \underline{U}_0)}{s^*} > 0.$$

Proposition 2 shows that the central insight of the model is robust to arbitrary divisions of bargaining power. Bargaining affects only how relationship surplus is divided between the dealer and the client. The spread continues to maximize joint surplus and therefore remains independent of the client's outside option. Platform adoption raises the client's outside option and thus the utility that must be delivered within the relationship. For any $\theta < 1$, this adjustment is absorbed entirely through larger primary-market allocations, while the spread remains unchanged. The baseline model corresponds to the special case $\theta = 0$, in which the dealer captures all surplus beyond the client's reservation value. Proofs are provided in the Internet Appendix.

In sum, the model provides a theoretical explanation for why platform adoption does not affect secondary-market outcomes. Instead, it predicts that dealers respond through the primary market. Next, we therefore examine whether clients receive larger primary-market allocations from relationship dealers following platform adoption.

6 Testing for primary-market effects of platform adoption

We now turn to the primary market (PM) and examine the central prediction of the model. Specifically, we test whether platform adoption increases clients' primary-market allocations. Following Nikolova, Wang, and Wu (2020), we identify a primary-market allocation as a purchase by a client from the underwriting dealer on the offering date at the offering price.

As in the secondary-market analysis, we exploit variation within client × dealer pairs and study how allocations within a given client-dealer relationship change following the client's adoption of the platform. We construct a panel at the client × dealer × asset-offering level over the one-year window before and after a client's adoption date, analogous to our secondary-market analysis, and

estimate the following specification:

$$Y_{c,d,a} = \beta \times PostAdoption_{c,a} + \alpha_{c\times d} + \alpha_{yq} + \epsilon_{c,d,a}, \tag{18}$$

where $Y_{c,d,a}$ denotes a primary-market outcome for client c, dealer d, and asset a. The indicator variable $PostAdoption_{c,a}$ equals one if the offering of asset a occurs after client c's platform adoption and zero beforehand. As before, the coefficient β captures the effect of platform adoption on primary-market allocations within a given client-dealer relationship. We additionally include year-quarter fixed effects, α_{yq}, and cluster standard errors at the client level.

6.1 PM: allocations increase

We begin by examining allocation quantities and estimate equation (18) with $Allocation_{c,d,a}$, the dollar amount allocated to client c by dealer d in asset a, as the dependent variable. We find a positive and statistically significant β coefficient of approximately \$1 million ($|t| > 2.4$); see column (1) of Table 5. In column (2), we use the normalized allocation, $\frac{Allocation_{c,d,a}}{\overline{A}_{c,d}}$, as the dependent variable, where $\overline{A}_{c,d}$ denotes the average pre-adoption primary-market allocation within the client-dealer relationship. The estimated effect implies that the client's allocation from the same dealer increases by 29% ($|t| > 3.0$) relative to the pre-adoption period.

TABLE 5 ABOUT HERE

In column (3), we use the total offering amount of the issue as the dependent variable to rule out the possibility that the results are driven by larger issuance sizes. The estimated coefficient is statistically insignificant. In column (4), we further test whether relationship dealers underwrite larger amounts following platform adoption. Specifically, we use as the dependent variable the total amount allocated in the same asset by the dealer to all of her clients on the issuance day. Once again, we find no statistically significant effect.

Taken together, these results indicate that clients receive substantially larger primary-market allocations from relationship dealers following platform adoption. These findings support the

central prediction of the model: following platform adoption, relationship dealers compensate clients through the PM rather than through the SM.

Bargaining power heterogeneity. We provide an additional test of the mechanism implied by the model. Proposition 2 predicts that the effects of platform adoption on primary-market allocations should be stronger for clients with lower bargaining power and weaker for clients with higher bargaining power. The intuition is that equilibrium allocations are more sensitive to changes in the client's outside option when the client's bargaining power is lower.

To assess a client's bargaining power vis-à-vis a relationship dealer, we exploit a revealed-preference implication of Proposition 2: pre-adoption allocations are lower (higher) when a client has less (more) bargaining power. We therefore compute, for each client-dealer relationship, the share of the client's total pre-adoption primary-market allocations received from that dealer. We then split the sample into relationships with low (below-median) and high (above-median) bargaining power.

TABLE 6 ABOUT HERE

We estimate equation (18) using the normalized allocation, $\frac{Allocation_{c,d,a}}{\overline{A}_{c,d}}$, introduced above as the dependent variable. This normalization allows us to compare the estimated sensitivities across the two groups. The results are reported in Table 6 and confirm the model's prediction: primary-market allocations are less sensitive to platform adoption for clients with greater bargaining power (column (1)) than for clients with lower bargaining power (column (2)). The estimated increase amounts to 18% ($|t| > 2.6$) for clients with greater bargaining power, compared with 52% ($|t| > 2.6$) for clients with lower bargaining power.[3]

Next, we investigate whether the larger primary-market allocations received after platform adoption translate into meaningful gains for clients.

[3]Table IA.V in the Internet Appendix reports a robustness test. Rather than splitting the sample at the median, we classify relationships into low- and high-bargaining-power groups within each client. The results are robust: relationships with lower bargaining power exhibit a greater sensitivity of primary-market allocations to platform adoption than relationships with higher bargaining power. We further use alternative definitions, such as the client's total pre-adoption allocation relative to the underwriter's total pre-adoption allocations. The results remain robust.

6.2 PM: larger allocations translate into greater profits

Our finding that dealers allocate larger amounts to relationship clients suggests that these clients also experience greater profits, given the presence of underpricing at issuance.[4] To examine this, we define the following measure:

$$Profit_{c,d,a,T} = Allocation_{c,d,a} \times UP_{a,T}, \tag{19}$$

where $Allocation_{c,d,a}$ denotes the dollar allocation from the previous section, and $UP_{a,T}$ is a measure of underpricing at issuance (defined below). Having established that allocation quantities increase following platform adoption, we next focus on underpricing, the second key determinant of $Profit$.

Access to underpriced bonds is an important source of value for investors. Consequently, platform adoption may affect not only the quantity of allocations but also their quality, with relationship dealers potentially allocating more underpriced bonds to clients following adoption. To examine this possibility, we compute underpricing as follows:

$$UP_{a,T} = \ln(P_{a,T}) - \ln(P_a^{Off}), \tag{20}$$

where $P_{a,T}$ denotes the volume-weighted average TRACE transaction price of asset a measured T days after issuance, and P_a^{Off} is the offering price of a. Table IA.VI in the Internet Appendix reports summary statistics for $UP_{a,T}$ across different horizons T. Average underpricing on the offering day (i.e. $T = 0$) is around 28 basis points and increases to about 36 basis points over the subsequent 3–5 trading days. These magnitudes are consistent with those documented in the literature (see, e.g., Nikolova, Wang, and Wu, 2020).[5]

[4] Several studies document the presence of underpricing; see, among others, Cai, Helwege, and Warga (2007), Nikolova, Wang, and Wu (2020), Wang (2021), Bessembinder et al. (2022), and Siani (2025).

[5] Notably, this level of underpricing is comparable in magnitude to average transaction costs in the secondary market (see, e.g., Bessembinder, Spatt, and Venkataraman, 2020, for a detailed survey). Our sample exhibits a similar pattern: average price discrimination is approximately 36 basis points, while underpricing ranges from 28 to 35 basis points. This similarity supports the model's implicit assumption that underpricing and secondary-market trading spreads are of comparable magnitude.

TABLE 7 ABOUT HERE

Next, to test whether dealers allocate more underpriced assets to clients following platform adoption, we estimate equation (18) using $UP_{a,T}$ as the dependent variable. Focusing on the horizon $T = 0$, we obtain a positive but statistically insignificant β coefficient, indicating that dealers do not systematically allocate more underpriced bonds to clients following platform adoption–see column (1) Table 7. This finding is consistent with the model, which predicts that dealers respond to platform adoption by adjusting allocation quantities, a, rather than spreads, s

In the next step, we focus on profits and estimate equation (18) using $Profit_{c,d,a,T}$ with $T = 0$ as the dependent variable. The results are reported in column (2) of Table 7. We obtain a positive and statistically significant β coefficient ($|t| > 2.6$), implying an increase in $Profit$ of approximately \$4,106 following a client's platform adoption.

It is worth noting that the increase in $Profit$ following platform adoption provides a revealed-preference measure of the increase in a client's outside option. According to Proposition 1, $\underline{U}_1 - \underline{U}_0 = (a_1^* - a_0^*)s^*$, which links the adoption-induced increase in the client's outside option to the increase in primary-market allocations multiplied by the spread. The observed increase in $Profit$ therefore provides empirical support for the mechanism highlighted by the model and can be interpreted as the economic value of platform adoption.

To quantify this value, we estimate equation (18) using the normalized profit, $\frac{Profit_{c,d,a}}{\overline{P}_{c,d}}$, as the dependent variable, where $\overline{P}_{c,d}$ denotes the average pre-adoption primary-market profit within the client-dealer relationship. The estimated effect implies that, for the average client, platform adoption is worth 77% ($|t| > 4.1$) of pre-adoption profits from primary-market allocations. This magnitude suggests that platform adoption generates economically meaningful benefits.

6.3 PM: excluding alternative explanations

In this section, we examine whether platform adoption is associated with changes in other dimensions of primary-market allocations. We begin by examining access to new asset types. Specifically, analogous to the analysis in the SM, we test whether post-adoption allocations are more likely to

involve assets that had not previously been allocated to the client. To do so, we define the dependent variable $Y_{c,d,a}$ in equation (18) as an indicator equal to one if client c receives an allocation from dealer d in asset a issued by an issuer from whom the client had not received any allocation during the preceding three- or five-year period.

Columns (1) and (2) of Table IA.VII in the Internet Appendix report the results. The estimated coefficients are statistically insignificant in both specifications. Hence, following platform adoption, clients are no more likely to receive allocations from relationship dealers in assets that had not previously been allocated to them, providing no evidence that platform adoption expands access to new assets through existing dealer relationships.

Next, we examine two additional asset dimensions: allocations in illiquid assets and high-yield bonds. We define illiquid assets analogously to the secondary-market analysis using a turnover-based indicator. Column (3) shows no significant effect on the likelihood of receiving allocations in illiquid assets. Column (4) similarly shows no significant effect on allocations in high-yield bonds. Overall, we find no evidence that platform adoption expands clients' access to different types of primary-market assets.

In the final step, we focus on flipping–that is, immediately unwinding a primary-market allocation in the secondary market. Flipping is a common practice (see, e.g., Nikolova and Wang, 2022) that allows investors to realize the gains from underpricing. Platform adoption could therefore increase clients' propensity to flip allocations.

To examine this possibility, we again estimate equation (18) and define the dependent variable $Y_{c,d,a}$ as an indicator equal to one if the allocation is flipped and zero otherwise. The results are reported in Table IA.VII in the Internet Appendix. Column (5) examines whether the allocation is flipped with any dealer within 15 days of the offering date, whereas column (6) restricts attention to flips executed with the focal dealer d. In both specifications, the estimated β coefficients are statistically insignificant, providing no evidence that platform adoption increases clients' propensity to flip allocations.

In sum, our findings suggest that relationship dealers respond to the increase in clients' outside

options following platform adoption by adjusting primary-market allocation quantities rather than secondary-market trading terms.

7 Conclusion

This paper studies how centralized trading platforms affect client-dealer relationships in OTC markets. While the conventional view is that platforms improve transaction terms by intensifying competition, we find no empirical evidence that platform adoption alters a client's outcomes in the secondary market. Instead, the effects emerge in the primary market, where relationship dealers respond by granting larger allocations to clients.

We show that these findings align with a simple model of vertically integrated dealers that operate in both the primary and secondary markets. The model highlights that dealers can respond to clients' improved outside options through different margins. Because primary-market allocations act as a transfer mechanism, the optimal response is to adjust allocations rather than secondary-market trading terms. Our empirical results provide strong support for this mechanism.

More broadly, our findings suggest that the effects of trading platforms cannot be understood by studying individual markets in isolation. Changes in competition in one market may induce adjustments in another market when intermediaries operate across both. Understanding the consequences of market design and technological innovation therefore requires taking these cross-market interactions into account.

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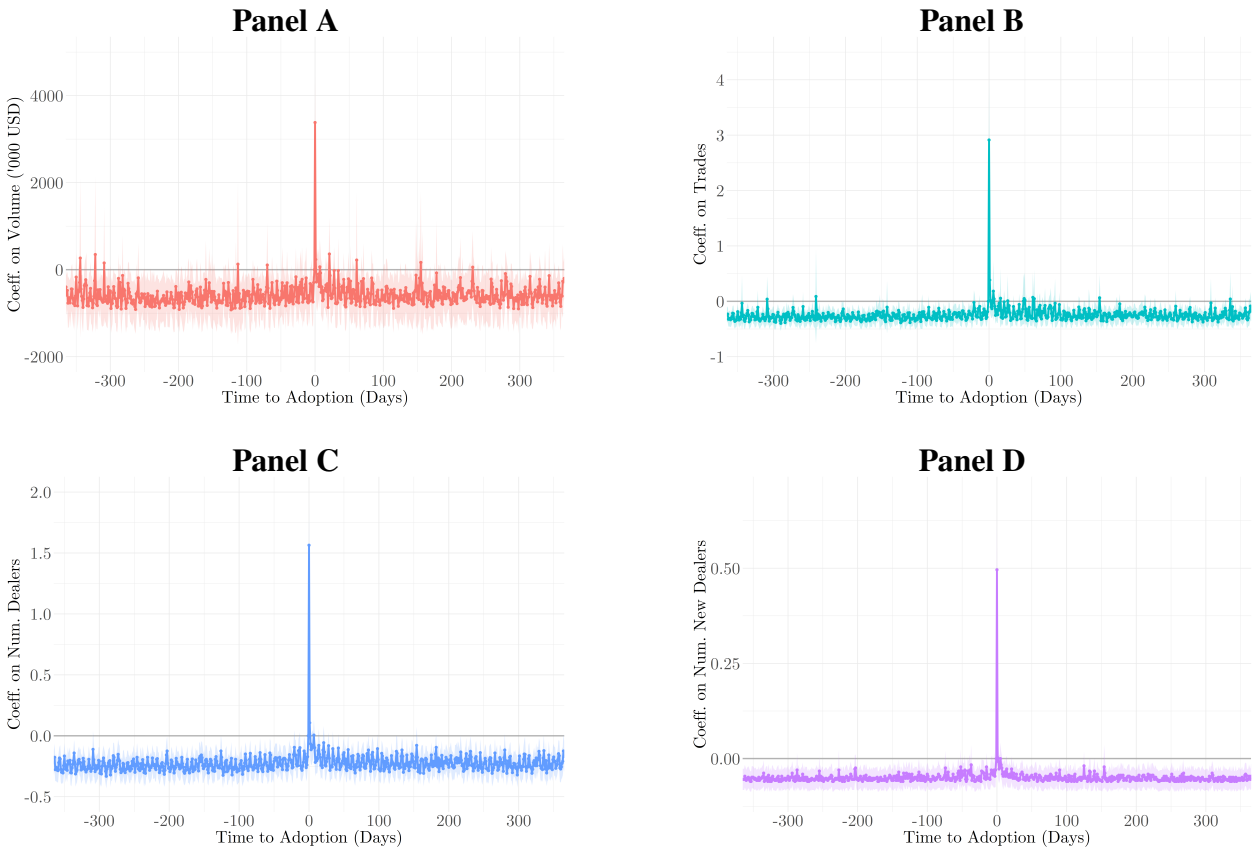


Figure 1: Identifying platform adoption. This figure reports the event-time coefficients, β_s, from the regression $Y_{c,k_c+s} = \sum_s \beta_s \times \mathbb{I}_{c,k_c+s} + \alpha_c + \epsilon_{c,k_c+s}$, where Y_{c,k_c+s} denotes a bilateral secondary-market trading outcome for client c on day $k_c + s$, relative to the client's first OT trade date k_c (i.e. event day); $\mathbb{I}_{c,k_c+s}$ is an indicator equal to one on day $k_c + s$; and α_c denotes client fixed effects. The event window is $s \in [-365, 365]$, with $s = -1$ as the omitted reference day. Standard errors are clustered at the client level. Panel A reports trading volume, Panel B the number of trades, Panel C the number of dealers, and Panel D the number of new dealers. The shaded area represents 95% confidence intervals. The sample consists of Schedule D filings from the NAIC covering 2006Q1–2019Q4.

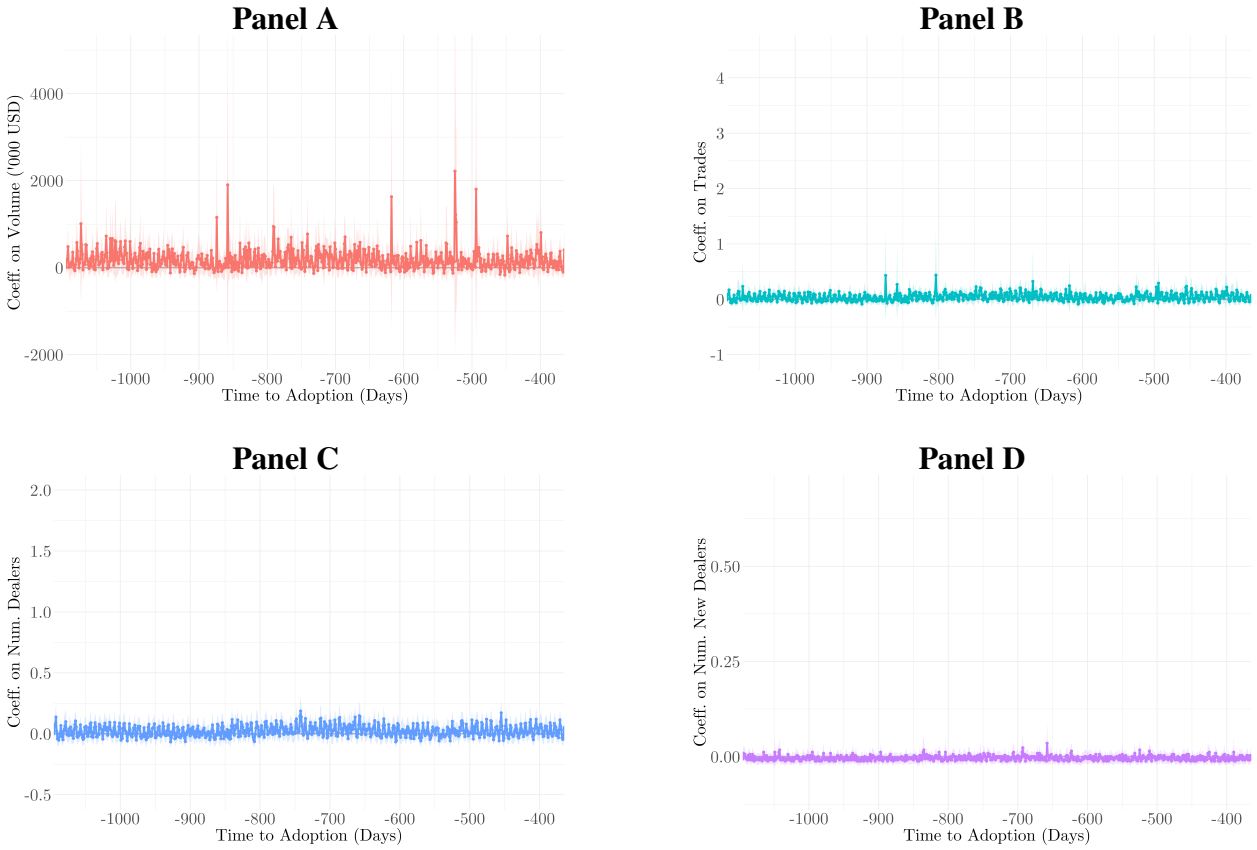


Figure 2: Placebo: identifying platform adoption. This figure reports the event-time coefficients, β_s, from the regression $Y_{c,k_c+s} = \sum_s \beta_s \times \mathbb{I}_{c,k_c+s} + \alpha_c + \epsilon_{c,k_c+s}$, where Y_{c,k_c+s} denotes a bilateral secondary-market trading outcome for client c on day $k_c + s$, relative to the client's first OT trade date k_c (i.e. event day); $\mathbb{I}_{c,k_c+s}$ is an indicator equal to one on day $k_c + s$; and α_c denotes client fixed effects. The event window is $s \in [-1095, -365]$, with $s = -731$ as the omitted reference day. Standard errors are clustered at the client level. Panel A reports trading volume, Panel B the number of trades, Panel C the number of dealers, and Panel D the number of new dealers. The shaded area represents 95% confidence intervals. The data are obtained from Schedule D filings of the NAIC covering 2006Q1–2019Q4.

Table 1: Summary statistics. We report summary statistics for our data aggregated at different levels. Panel A reports data aggregated at the client × dealer × trading-day level in the secondary market (SM), Panel B at the individual transaction record in the SM, and Panel C at the client × dealer × offering level in the primary market (PM). Price discrimination is measured relative to the best observed transaction price; see Section 4.2 for details. The data are obtained from Schedule D filings of the NAIC covering 2006Q1–2019Q4.

Variable	Observations	Mean	Median	Std. Dev.
Panel A: Client-Dealer-Trading Day SM				
Volume ('000 USD)	41 032	2663.37	1000.00	6072.26
Trades	41 032	1.30	1.00	1.78
Assets	41 032	1.22	1.00	1.48
Panel B: Individual Transaction SM				
Price Discrimination (Best)	21 104	0.36	0.27	0.62
Panel C: Client-Dealer-Allocation PM				
Allocation ('000 USD)	13 884	5098.63	1903.00	10 326.61
Profit	13 607	13 567.20	2163.90	45 662.50

Table 2: Trading volume in secondary market. This table reports the results from the regression $Y_{c,d,t_c} = \beta \times PostAdoption_{c,t_c} + \alpha_{c\times d} + \alpha_{yq} + \epsilon_{c,d,t_c}$, using data at the client × dealer × trading day from the one-year window before and after client c's platform adoption. Here, c indexes clients, d dealers, and t_c denotes client c's trading day. $PostAdoption_{c,t_c}$ is an indicator equal to one after client c adopts the platform and zero beforehand. $\alpha_{c\times d}$ and α_{yq} denote client × dealer and year-quarter fixed effects, respectively. The dependent variable Y_{c,d,t_c} is trading volume–in column (1) we use all days in the event window while in column (2) we exclude the adoption day; see Section 4.1 for details. t-statistics based on standard errors clustered at the client level are reported in parentheses. The data are obtained from Schedule D filings of the NAIC covering 2006Q1–2019Q4. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
	Volume	
PostAdoption	113.022	74.399
	[0.694]	[0.437]
Obs.	41032	40319
FE: client × dealer	X	X
FE: year × quarter	X	X

Table 3: Price discrimination in secondary market. This table reports the results from the regression $Y_{c,d,a,t_c} = \beta \times PostAdoption_{c,t_c} + \alpha_{c\times d} + \alpha_{a\times yq} + \epsilon_{c,d,a,t_c}$, using individual transaction records from the one-year window before and after client c's platform adoption. Here, c indexes clients, d dealers, a assets, and t_c denotes client c's trading day. $PostAdoption_{c,t_c}$ is an indicator equal to one after client c adopts the platform and zero beforehand. $\alpha_{c\times d}$ and $\alpha_{a\times yq}$ denote client $\times$ dealer and asset $\times$ year-quarter fixed effects, respectively. The dependent variable Y_{c,d,a,t_c} varies across specifications and is indicated in the column headings; see Section 4.2 for details. t-statistics based on standard errors clustered at the client level are reported in parentheses. The data are obtained from Schedule D filings of the NAIC covering 2006Q1–2019Q4. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	$PD(Best)$	$PD(Mid)$	$PD(Intd)$	$Trns.Amt.$
$PostAdoption$	−0.004	−0.013	0.001	90.530
	[−0.137]	[−0.480]	[0.021]	[0.400]
Obs.	21104	21104	21104	21104
FE: client × dealer	X	X	X	X
FE: asset × year × quarter	X	X	X	X

Table 4: Asset access in secondary market. This table reports the results from the regression $Y_{c,d,a,t_c} = \beta \times PostAdoption_{c,t_c} + \alpha_{c\times d} + \alpha_{yq} + \epsilon_{c,d,a,t_c}$, using individual transaction records from the one-year window before and after client c's platform adoption. Here, c indexes clients, d dealers, a assets, and t_c denotes client c's trading day. $PostAdoption_{c,t_c}$ is an indicator equal to one after client c adopts the platform and zero beforehand. $\alpha_{c\times d}$ and α_{yq} denote client × dealer and year-quarter fixed effects, respectively. The dependent variable Y_{c,d,a,t_c} varies across specifications and is indicated in the column headings; see Section 4.3 for details. t-statistics based on standard errors clustered at the client level are reported in parentheses. The data are obtained from Schedule D filings of the NAIC covering 2006Q1–2019Q4. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	Pr($New\ 3Y$)	Pr($New\ 5Y$)	Pr($Illiq$)	Pr(HY)
$PostAdoption$	−0.012	−0.009	−0.013	0.005
	[−1.017]	[−0.798]	[−1.269]	[0.280]
Obs.	50081	50081	50081	50081
FE: client × dealer	X	X	X	X
FE: year × quarter	X	X	X	X

Table 5: Primary market allocations. This table reports the results from the regression $Y_{c,d,a} = \beta \times PostAdoption_{c,a} + \alpha_{c\times d} + \alpha_{yq} + \epsilon_{c,d,a}$, using data at the client × dealer × asset-offering level from the one-year window before and after client c's platform adoption. Here, c indexes clients, d dealers, and a assets (offerings). $PostAdoption_{c,a}$ equals one if the offering of asset a occurs after client c's platform adoption and zero beforehand. $\alpha_{c\times d}$ and α_{yq} denote client × dealer and year-quarter fixed effects, respectively. The dependent variable $Y_{c,d,a}$ varies across specifications and is indicated in the column headings; see Section 6.1 for details. t-statistics based on standard errors clustered at the client level are reported in parentheses. The data are obtained from Schedule D filings of the NAIC covering 2006Q1–2019Q4. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	$Allocation$	$Allocation/\overline{A}$	$Off.Amt.$	$UW.Amt.$
$PostAdoption$	1002.445**	0.291***	49.298	1.371
	[2.443]	[3.081]	[0.398]	[0.189]
Obs.	13884	13884	13884	13884
FE: client × dealer	X	X	X	X
FE: year × quarter	X	X	X	X

Table 6: Primary market allocations: heterogeneity in bargaining power. This table reports the results from the regression $Y_{c,d,a} = \beta \times PostAdoption_{c,a} + \alpha_{c\times d} + \alpha_{yq} + \epsilon_{c,d,a}$, using data at the client × dealer × asset-offering level from the one-year window before and after client c's platform adoption. Here, c indexes clients, d dealers, and a assets (offerings). $PostAdoption_{c,a}$ equals one if the offering of asset a occurs after client c's platform adoption and zero beforehand. $\alpha_{c\times d}$ and α_{yq} denote client × dealer and year-quarter fixed effects, respectively. The dependent variable, $Y_{c,d,a}$, is the allocation divided by the client's average pre-adoption allocation. Column (1) reports results for clients with high bargaining power, and column (2) for clients with low bargaining power; see Section 6.1 for details. t-statistics based on standard errors clustered at the client level are reported in parentheses. The data are obtained from Schedule D filings of the NAIC covering 2006Q1–2019Q4. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
	$Allocation/\overline{A} \mid \overline{\theta}$	$Allocation/\overline{A} \mid \underline{\theta}$
$PostAdoption$	0.182***	0.515***
	[2.612]	[2.690]
Obs.	8941	4943
FE: client × dealer	X	X
FE: year × quarter	X	X

Table 7: Profits in primary market. This table reports the results from the regression $Y_{c,d,a} = \beta \times PostAdoption_{c,a} + \alpha_{c\times d} + \alpha_{yq} + \epsilon_{c,d,a}$, using data at the client × dealer × asset-offering level from the one-year window before and after client c's platform adoption. Here, c indexes clients, d dealers, and a assets (offerings). $PostAdoption_{c,a}$ equals one if the offering of asset a occurs after client c's platform adoption and zero beforehand. $\alpha_{c\times d}$ and α_{yq} denote client × dealer and year-quarter fixed effects, respectively. The dependent variable $Y_{c,d,a}$ varies across specifications and is indicated in the column headings; see Section 6.2 for details. t-statistics based on standard errors clustered at the client level are reported in parentheses. The data are obtained from Schedule D filings of the NAIC covering 2006Q1–2019Q4. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
	UP	$Profit$	$Profit/\overline{P}$
$PostAdoption$	0.018	4106.020***	0.768***
	[1.133]	[2.648]	[4.129]
Obs.	13607	13607	13607
FE: client × dealer	X	X	X
FE: year × quarter	X	X	X

Internet Appendix for

"Shadow Discounts"

Tomy Lee, Isacco Lotti, Florian Nagler, Giorgio Ottonello, and Chaojun Wang[1]

[1]Tomy Lee, Isacco Lotti, Florian Nagler, Giorgio Ottonello, and Chaojun Wang, Internet Appendix to "Shadow Discounts."

Model

Proof of Proposition 2. Because trading is not contractible, an agreement specifies only a spread s and an allocation a, while trading volume is subsequently chosen according to the client's optimal demand $D(s)$. For a given agreement (s, a), the client's utility is

$$\mathcal{U}_p(s, a) = sa + U(s, D(s)),$$

while the dealer's profit is

$$\Pi(s, a) = sD(s) - sa.$$

Hence, joint surplus is

$$\mathcal{U}_p(s, a) + \Pi(s, a) = sD(s) + U(s, D(s)).$$

Since the allocation is a transfer between the parties, it does not affect joint surplus. By definition,

$$W = \max_{s>0} \{sD(s) + U(s, D(s))\}.$$

Therefore, every efficient bargaining outcome selects a spread that attains W. The set of such spreads coincides with the set of optimal spreads characterized in Proposition 1.

Let $\underline{U}_p$ denote the client's outside option. Along the efficient frontier,

$$\mathcal{U}_p + \Pi = W,$$

so that

$$\Pi = W - \mathcal{U}_p.$$

Hence, the bargaining problem can be written as a choice over the client's utility alone. The

generalized Nash bargaining solution therefore solves

$$\max_{\mathcal{U}_p \in [\underline{U}_p, W]} \left(\mathcal{U}_p - \underline{U}_p\right)^{\theta} \left(W - \mathcal{U}_p\right)^{1-\theta}.$$

For $\theta \in (0, 1)$, the first-order condition is

$$\frac{\theta}{\mathcal{U}_p - \underline{U}_p} = \frac{1-\theta}{W - \mathcal{U}_p},$$

which implies

$$\theta(W - \mathcal{U}_p) = (1-\theta)(\mathcal{U}_p - \underline{U}_p).$$

Solving yields

$$\mathcal{U}_p = \underline{U}_p + \theta(W - \underline{U}_p).$$

The same expression obtains at the boundary cases. When $\theta = 0$, the client receives its outside option, $\mathcal{U}_p = \underline{U}_p$. When $\theta = 1$, the client receives the entire joint surplus, $\mathcal{U}_p = W$.

Let $s^* > 0$ denote any selected optimal spread. The allocation must satisfy

$$s^* a_p^{\theta} + U(s^*, D(s^*)) = \underline{U}_p + \theta(W - \underline{U}_p).$$

Solving for a_p^{θ} gives

$$a_p^{\theta} = \frac{\underline{U}_p + \theta(W - \underline{U}_p) - U(s^*, D(s^*))}{s^*}.$$

Finally, for any common selected optimal spread $s^* > 0$,

$$a_1^{\theta} - a_0^{\theta} = \frac{\underline{U}_1 - \underline{U}_0 + \theta(\underline{U}_0 - \underline{U}_1)}{s^*} = \frac{(1-\theta)(\underline{U}_1 - \underline{U}_0)}{s^*}.$$

Since $\underline{U}_1 > \underline{U}_0$, it follows that

$$a_1^{\theta} - a_0^{\theta} > 0$$

for every $\theta \in [0, 1)$. □

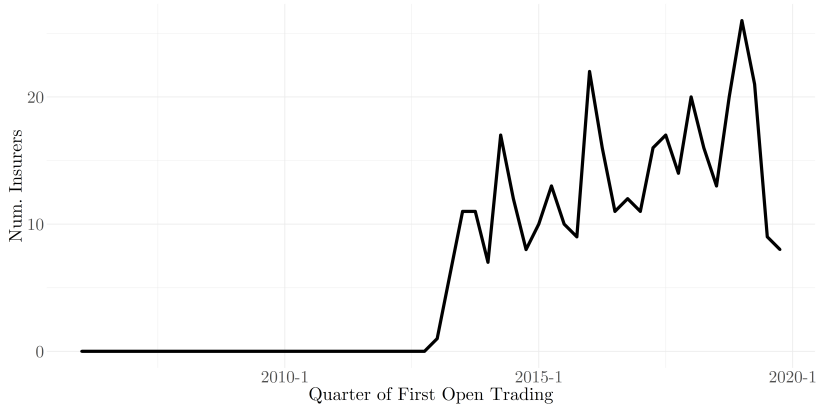


Figure IA.1: Adoption events over time. This figure plots the number of platform adoption events by calendar quarter, where adoption is identified as the client's first OT trade. The sample consists of Schedule D filings from the NAIC covering 2006Q1–2019Q4.

Table IA.I: Asset managers. This table reports the asset managers of insurers and the number of funds managed by each in our sample. Asset managers are identified using the insurer's parent name. The data are obtained from Schedule D filings of the NAIC covering 2006Q1–2019Q4.

Parent Name	Funds
Deutsche Asset Management	272
BlackRock, Inc.	250
Conning Asset Management Co	232
General Re-New England Asset Management, Inc.	211
Asset Allocation & Management Co LLC	138
Wellington Management Company, LLP	137
Standish Mellon Asset Management Co LLC	67
Prime Advisors Inc	60
J.P. Morgan Asset Management Inc	56
Prudential Global Asset Management	49
Pacific Investment Management Co LLC PIMCO	47
Brookfield Investment Management Inc	46
Goldman Sachs Asset Management LP	46
Western Asset Management Co	44
Tattersall Advisory Group Inc	37
Wells Capital Management Inc	36
Madison Investment Advisors Inc	34
McDonnell Investment Management LLC	34
Morgan Stanley Investment Management Inc	33
Zazove Associates LLC	33
Columbia Management - Ameriprise	32
Advantus Capital Management Inc	31
Brown Brothers Harriman & Co.	27
Income Research & Management Inc	26
Neuberger Berman LLC	26
Northern Trust Global Advisors Inc	25
Sage Advisory Services Ltd Co	25
Shenkman Capital Management Inc	23
State Street Global Advisors	23
Alliance Capital Management L.P.	22
PineBridge Investments LLC	21
GE Asset Management Inc	20
Travelers Asset Management	19
Baird Advisors	18
Mellon Bond Associates	18
Guggenheim Investment Management LLC	17
Vanguard Group Inc, The	17
Prospector Partners LLC	15
Fidelity National Financial	14
Cutwater Asset Management Corp	13
Fort Washington Investment Advisors Inc.	13
INVESCO Inc	13
Delaware Investments	12

Parent Name	Funds
NISA Investment Advisors LLC	12
Sterling Capital Management LLC	12
Calamos Advisors LLC	11
Phoenix Investment Partners	11
TCW Asset Management Co TAMCO	11
Eagle Asset Management Inc	10
Loomis, Sayles & Company L.P.	10
Lord, Abbett & Company	10
Harris Investment Management Inc	9
Logan Capital Management Inc	9
Manning & Napier Advisors Inc	9
Merrill Lynch Investment Managers	9
Spectrum Asset Management Inc	9
STW Fixed Income Management Ltd.	9
BofA Advisors LLC	8
Companion Capital Management, Inc.	8
Flaherty & Crumrine Inc	8
Lazard Asset Management LLC	8
Northern Capital	8
Principal Global Investors Fixed Income	8
Sit Investment Associates, Inc	8
Alpha Advisors Inc.	7
Dimensional Fund Advisors LP	7
Dodge & Cox Inc	7
Eaton Vance Management	7
NWQ Investment Management Co LLC	7
Parkway Advisors	7
MacKay Shields LLC	6
Aberdeen Asset Management	5
Fidelity Management & Research Company	5
Household International, Inc.	5
TD Banknorth Wealth Management Group	5
William Blair & Co LLC	5
C S McKee LP	4
Crdit Suisse Asset Management Americas	4
Lee Munder Capital Group	4
UBS Global Asset Management	4
National City Investment Management Company	3
Chase Investment Counsel Corp	2
Mellon Capital Management Corp	2
OakTree Capital Management LP	2
Citigroup Alternative Investments LLC	1

Table IA.II: Robustness: trading activity based on balanced sample. This table reports the results from the regression $Y_{c,d,t} = \beta \times PostAdoption_{c,t_c} + \alpha_{c\times d} + \alpha_{yq} + \epsilon_{c,d,t_c}$, using data at the client × dealer × day from the one-year window before and after client c's platform adoption. Here, c indexes clients, d dealers, and t denotes days. $PostAdoption_{c,t}$ is an indicator equal to one after client c adopts the platform and zero beforehand. $\alpha_{c\times d}$ and α_{yq} denote client × dealer and year-quarter fixed effects, respectively. The dependent variable $Y_{c,d,t}$ is an indicator: if client c trades with dealer d on day t, the indicator equals one; otherwise, it equals zero; see Section 4.1 for details. t-statistics based on standard errors clustered at the client level are reported in parentheses. The data are obtained from Schedule D filings of the NAIC covering 2006Q1–2019Q4. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(2)
	$\Pr(Trade)$
$PostAdoption$	−0.001
	[−1.000]
Obs.	949013
FE: client × dealer	X
FE: year × quarter	X

Table IA.III: Robustness: price discrimination in secondary market. This table reports the results from the regression $Y_{c,d,a,t_c} = \beta \times PostAdoption_{c,t_c} + \alpha_{c\times d} + \alpha_{a\times yq} + \epsilon_{c,d,a,t_c}$, using individual transaction records from the one-year window before and after client c's platform adoption. Here, c indexes clients, d dealers, a assets, and t_c denotes client c's trading day. $PostAdoption_{c,t_c}$ is an indicator equal to one after client c adopts the platform and zero beforehand. $\alpha_{c\times d}$ and $\alpha_{a\times yq}$ denote client × dealer and asset × year-quarter fixed effects, respectively. We exclude the adoption day from the sample. The dependent variable Y_{c,d,a,t_c} varies across specifications and is indicated in the column headings; see Section 4.2 for details. t-statistics based on standard errors clustered at the client level are reported in parentheses. The data are obtained from Schedule D filings of the NAIC covering 2006Q1–2019Q4. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	$PD(Best)$	$PD(Mid)$	$PD(Intd)$	$Trns.Amt.$
$PostAdoption$	−0.001	−0.010	0.008	98.320
	[−0.026]	[−0.346]	[0.290]	[0.400]
Obs.	20563	20563	20563	20563
FE: client × dealer	X	X	X	X
FE: asset × year × quarter	X	X	X	X

Table IA.IV: Volume splitting and trade performance. This table reports the results from the regression $Y_{c,d,a,t_c} = \beta \times PostAdoption_{c,t_c} + \alpha_{c\times d} + \alpha_{yq} + \epsilon_{c,d,a,t_c}$, using individual transaction records from the one-year window before and after client c's platform adoption. Here, c indexes clients, d dealers, a assets, and t_c denotes client c's trading day. $PostAdoption_{c,t_c}$ is an indicator equal to one after client c adopts the platform and zero beforehand. $\alpha_{c\times d}$ and α_{yq} denote client $\times$ dealer and year-quarter fixed effects, respectively. The dependent variable Y_{c,d,a,t_c} varies across specifications and is indicated in the column headings; see Section 4.2 for details. t-statistics based on standard errors clustered at the client level are reported in parentheses. The data are obtained from Schedule D filings of the NAIC covering 2006Q1–2019Q4. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	$\Pr(Split)$		$Performance$	
		$T \in [1, 10]$	$T \in [11, 20]$	$T \in [21, 30]$
$PostAdoption$	0.018	−0.029	−0.011	−0.012
	[1.599]	[−1.606]	[−0.433]	[−0.344]
Obs.	27895	27895	27895	27895
FE: year × quarter	X	X	X	X
FE: client × dealer	X	X	X	X

Table IA.V: Robustness: primary market allocations and heterogeneity in bargaining power. This table reports the results from the regression $Y_{c,d,a} = \beta \times PostAdoption_{c,a} + \alpha_{c\times d} + \alpha_{yq} + \epsilon_{c,d,a}$, using data at the client × dealer × asset-offering level from the one-year window before and after client c's platform adoption. Here, c indexes clients, d dealers, and a assets (offerings). $PostAdoption_{c,a}$ equals one if the offering of asset a occurs after client c's platform adoption and zero beforehand. $\alpha_{c\times d}$ and α_{yq} denote client × dealer and year-quarter fixed effects, respectively. The dependent variable, $Y_{c,d,a}$, is the allocation divided by the client's average pre-adoption allocation. Column (1) reports results for clients with high bargaining power, and column (2) for clients with low bargaining power; see Section 6.1 for details. t-statistics based on standard errors clustered at the client level are reported in parentheses. The data are obtained from Schedule D filings of the NAIC covering 2006Q1–2019Q4. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
	$Allocation/\overline{A} \mid \overline{\theta}$	$Allocation/\overline{A} \mid \underline{\theta}$
$PostAdoption$	0.183**	0.740**
	[2.367]	[2.351]
Obs.	10603	3281
FE: client × dealer	X	X
FE: year × quarter	X	X

Table IA.VI: Underpricing on primary market offerings. This table reports summary statistics for underpricing measured over various horizons following an asset's offering; see Section 6.2 for details. The data are obtained from Schedule D filings of the NAIC covering 2006Q1–2019Q4.

	(1)	(2)	(3)	(4)
		UP		
	$T = 0$	$T \in [0, 2]$	$T \in [3, 5]$	$T \in [6, 10]$
(Intercept)	0.282***	0.314***	0.356***	0.326***
	[15.978]	[18.692]	[26.867]	[24.299]
Obs.	13607	13512	12122	12350

Table IA.VII: Excluding alternative explanations: primary market. This table reports the results from the regression $Y_{c,d,a} = \beta \times PostAdoption_{c,a} + \alpha_{c\times d} + \alpha_{yq} + \epsilon_{c,d,a}$, using data at the client × dealer × asset-offering level from the one-year window before and after client c's platform adoption. Here, c indexes clients, d dealers, and a assets (offerings). $PostAdoption_{c,a}$ equals one if the offering of asset a occurs after client c's platform adoption and zero beforehand. $\alpha_{c\times d}$ and α_{yq} denote client × dealer and year-quarter fixed effects, respectively. The dependent variable $Y_{c,d,a}$ varies across specifications and is indicated in the column headings; see Section 6.3 for details. t-statistics based on standard errors clustered at the client level are reported in parentheses. The data are obtained from Schedule D filings of the NAIC covering 2006Q1–2019Q4. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Pr(New\ 3Y)$	$\Pr(New\ 5Y)$	$\Pr(Illiq)$	$\Pr(HY)$	$\Pr(Flip)$	$\Pr(Flip\|d)$
$PostAdoption$	−0.003	0.000	−0.015	0.009	−0.006	0.004
	[−0.172]	[0.016]	[−0.806]	[0.552]	[−0.561]	[0.467]
Obs.	13884	13884	13884	13884	13884	13884
FE: client × dealer	X	X	X	X	X	X
FE: year × quarter	X	X	X	X	X	X