

Tricks of the Trade? Pre-Issuance Price Maneuvers by Underwriter-Dealers*

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ABSTRACT

We study the trading of dealers around new bond issues underwritten by their affiliates using a complete matched record of U.S. bond market transactions, bond issue deals, and underwriter ownership structure from 2005 to 2015. Compared to dealers unaffiliated to the lead underwriter, affiliated dealers pay 16–40 basis points more for the issuer’s *preexisting* bonds—prior to, during, and after the issuance event. We interpret this phenomenon as cross-security price support and, prior to the event, price maneuvers aimed at lowering the reference yield for new issue investors. By examining dealer inventories and profits, we find no support for alternative explanations such as hedging, informed trading, or competitive advantage in market-making.

Keywords: Bond underwriting, Dealer market, Corporate bonds, Price support

JEL classification: G12, G14, G23, G24

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Financial institutions typically play multiple roles in capital markets. One notable example is that a dealer bank underwrites and intermediates securities at the same time. Previous literature has shown that, in equity markets, being affiliated with the underwriter of a security affects the trading behavior of a dealer of that security (Ellis, Michaely, and O’Hara, 2000). Affiliation may carry contractual obligations to the issuer, such as liquidity provision or price stabilization, and it may establish the dealer’s role as dominant market-maker of that security because of economies of scale. However, the role of underwriter-dealers in mediating a link between the primary market and the secondary market for *other* securities of the issuing firm is understudied. In this paper, we begin to fill this gap by investigating affiliated dealers’ trading behavior in the corporate bond market.¹ Unlike equity securities—the main focus of previous literature—most bond issuers issue multiple securities over time. Therefore, when a firm issues a new bond, it is common to have an active market for its previously issued bonds.

We ask whether any underwriting-induced motives spill over to the secondary market for an issuer’s existing bonds. Does the underwriter’s price support role extend to existing securities? Are there other motives that are specific to existing securities? For instance, the underwriter-dealer may hedge its exposure to the credit risk of the newly issued bond by short selling other existing bonds in the secondary market. Alternatively, private information about the issuer may leak from the underwriter to the dealer, allowing the latter to trade on the resulting informational advantage.

To answer these questions, we construct a complete dataset of underwriting events and bond transactions from 2005 to 2015. To the best of our knowledge, we are the first ones to use bank holding company information from the Federal Reserve System to manually link underwriters in the primary bond market with securities dealers in the secondary bond market. This novel ownership structure dataset enables us to merge the unmasked, regulatory version of TRACE trade data with a record of all firmly underwritten bond issues from Mergent FISD.

We find that in contemporaneous transactions, affiliated dealers pay significantly higher prices than unaffiliated dealers for existing bonds of the same issuer, *prior to*, during, and after the bond offering. The price difference is economically meaningful: 30 basis points at the peak for the average

¹Goldstein and Hotchkiss (2007) study dealers’ trading of new corporate bond issues, finding no evidence that dealers in newly issued bonds accumulate significant inventory positions.

bond, and up to roughly double for bonds with specific characteristics. We rule out the possibility that this result is driven by heterogeneity across dealers (e.g., size or market power of dealers) or across bonds (e.g., contract specification or liquidity). This “aggressive bidding” action typically starts in the month prior to the new bonds’ issue date, and lasts for roughly another five months afterwards.²

We argue that aggressive bidding is evidence of cross-security price support conducted by the affiliated dealers. It is common practice to make the bond issuance deal contingent upon the attainable borrowing cost, and the market yield of an issuer’s existing bonds is a primary reference point for the pricing of new bonds. Thus, issuer and underwriter incentives are aligned: price support lowers this reference point, increasing the likelihood that the issuance will be carried out and protecting the underwriter’s fee revenue.³ Consistent with this view, we find that the price difference is more pronounced for existing bonds that are more useful as benchmark, i.e., bonds whose remaining maturity is similar to that of the new issue and relatively more liquid bonds.

In general, supporting existing bond prices ahead of the issue is likely to help the issuing firm in securing a lower cost of capital relative to the one that would prevail without support. Lou, Yan, and Zhang (2013) show that the secondary market yields of preexisting U.S. Treasury bonds spike in the run-up to issuance events, representing an issuance cost of 9–18 basis points. Similarly, Corwin (2003) shows evidence of price pressure in the run-up to seasoned equity offerings. If this phenomenon exists in the liquid markets for Treasury bonds and equities, it is presumably even more important in the illiquid corporate bond market. Thus, the dealer’s intervention to manage existing bond prices before and after the issuance event may create substantial value for the issuer. The underwriter-driven inflated price reference may induce a wealth transfer from investors in the primary market to issuers.

Buy and sell transactions by affiliated dealers can be categorized by whether the counterparty is a dealer or a client. A large price difference is only consistently observed in buy transactions when facing other dealers. A more modest and marginally significant price difference is visible

²In order to have sufficient statistical power, we must lump our observations together into four-week months. Thus, we have evidence of aggressive bidding in the four weeks prior to the issue week, but we are unable to pinpoint the exact time within those four weeks in which the aggressive bidding begins.

³Baker, Pan, and Wurgler (2012) show that prior stock prices are used as reference in mergers, and merger offers’ likelihood of acceptance increases discontinuously if they exceed a prior peak price.

for buy and sell transactions facing clients. This suggests that affiliated dealers cannot always sell bonds at a higher price, even though they purchase them at a more aggressive price, and therefore conducting a cross-security price support operation can be costly. However, we find that the volume of client-facing transactions, on average, is much larger than that of inter-dealer trades, and therefore executing a pricing maneuver via inter-dealer trades can be more cost-efficient.

Furthermore, we show that the degree of aggressive bidding is associated with the importance of the issuer as a client. The difference between prices paid by affiliated and unaffiliated dealers becomes more pronounced when the issuer (the underwriters' client) has issued more and more frequently in the past. These heterogeneous results are consistent with underwriters' incentive to minimize their clients' cost of capital. Ljungqvist, Marston, and Wilhelm (2006) show that, in the presence of competition for underwriting mandates, the main determinant of lead-underwriter choice is the strength of past underwriting. Their finding helps us understand the underwriter-dealers' motivation to engage in pre-issuance price support.

In addition to the cross-security price support motive, other explanations of aggressive bidding are conceivable. These alternative explanations differ from the price support motive in their implications for dealer variables other than transaction prices, such as inventories and profits.

For instance, an underwriter's commitment to sell a new issue constitutes an implicit long position. To hedge the resulting exposure to the issuer, affiliated dealers may short-sell existing bonds relying on the correlation between prices of new and old bonds. In this case, aggressive bidding could be evidence of short covering, especially in the aftermath of the issuance event. However, we do not find any evidence that affiliated dealers accumulate abnormally negative inventory positions in the existing bonds in the run-up to the underwriting event. Rather, we observe that all dealers (affiliated and unaffiliated) provide liquidity by accumulating positive inventories starting in the event month, with affiliated dealers committing substantially more capital.

Alternatively, affiliated dealers may show an atypical trading pattern because they become a dominant market-maker for the security they underwrite. This phenomenon, first highlighted by Ellis et al. (2000), is also visible in our data with respect to trading of the newly issued bond. If the issuance event also enhances the dealer's status as a market-maker of the issuer's *existing* bonds,

the dealer may be able to sell bonds to clients and other dealers at a premium price, and as a consequence it may also be willing to make higher bids. If this is the case, the status enhancement should translate into an increase in the dealer’s market-making profits.

It is also possible that non-public information about the issuing firm leaks from underwriters to their affiliated dealers. A similar phenomenon is observed in the context of equity IPOs by Chiang, Lowry, and Qian (2018). In this case, when an underwriter learns some price-relevant information through the underwriting process, its affiliated dealer may act upon the informational advantage. If the dealer is more likely to act when the information is positive, aggressive bidding would reflect the dealer’s attempt to build a long position before the information becomes public at the time of issue. If this is the case, the information advantage should translate into an increase in the dealer’s position-taking profits.

To verify these two profit-related hypotheses, we construct a measure of dealers’ total trading profits directly from trade marks, and decompose it into short-term market-making profits and long-term position-taking profits. We find that both components of profits remain almost constant over the event window. This result is robust across several specifications, suggesting that neither the dealer’s enhanced status as a market-maker of existing bonds, nor information-driven trading are the main mechanisms that explain the aggressive bidding pattern. Also, this finding implies that the cost of pricing maneuvers through inter-dealer trades is not large enough to observe.

With respect to market making, we show that affiliated dealers do enjoy a boost in their status as a market-maker of existing bonds, but only at the time of the new bond issue. We show that, in the issue month, trading volume for an issuer’s existing bonds spikes, and the spike is about twice as high for affiliated dealers. We also show that affiliated dealers become more central to the dealer network in the event month, and interact more with large insurance companies. However, this boost is temporary and circumscribed—it happens only in the event month, and therefore it cannot explain aggressive bidding in the months after the event, let alone in the months before the event. Rather, the evidence we uncover by investigating alternative hypotheses is consistent with a “car dealership” role of underwriter-dealers: when a client buys a new bond, the dealer in that transaction may allow the client to trade-in an old bond, even though it may have originally been underwritten by a different entity. This is a related, but distinct, aspect of price support.

Our findings contribute to the literature on price dispersion in the bond market, documenting that transaction prices and execution quality are not uniform across investors and trades (Green, Hollifield, and Schürhoff, 2007; Goldstein, Hotchkiss, and Sirri, 2007; Biais and Green, 2007; O’Hara, Wang, and Zhou, 2017).⁴ The same market frictions that make price discrimination possible may also provide dealers with the capability to support prices as we document in our paper.

Our results also shed light on the role of securities dealers. Most previous literature focuses on the liquidity provision role of dealers in decentralized markets (Bao, O’Hara, and Zhou, 2018; Bessembinder, Jacobsen, Maxwell, and Venkataraman, 2018; Schultz, 2017). We show that their role is not limited to liquidity provision: they also make a significant difference for asset prices around issuance events. It is well-documented that price support on the security being underwritten is conducted by security underwriters (Gande, Puri, Saunders, and Walter, 1997; Aggarwal, 2000), and sometimes even by other affiliated intermediaries (Golez and Marin, 2015). However, our paper uncovers a new channel through which underwriters maneuver in the market: cross-security price support starting even before the new bond’s issue date.

It is well known that firms exhibit “market timing” behavior in corporate bond issues as well as in equity issues. Bond issuers may cancel the issue when the expected market yield of the new debt does not fall under some threshold.⁵ The aggressive bidding pattern by underwriters that we discover implies that financial intermediaries create additional price dynamics around the timing behavior of the issuer. More broadly, this paper contributes to a strand of literature about financial institutions’ multiple roles in the market (Drucker and Puri, 2005; Chen and Martin, 2011; Chiang et al., 2018), especially with regard to potential resulting conflicts of interest (Puri, 1996; Ljungqvist et al., 2006; Mola and Guidolin, 2009).

The road map of the paper is as follows. Before our empirical analysis, Section I describes our data in detail. Section II discusses our main finding of an aggressive bidding pattern. Sections III and IV show that the characteristics of the issues and issuers that are the target of aggressive bidding

⁴Specifically, O’Hara et al. (2017) document that different insurance companies pay different price for the same bond on the same day depending on how active they are as investors.

⁵As a recent example, Charter Communications canceled a \$1.5 billion issue on June 22, 2017. The cable operator, after initially hiring Credit Suisse as its underwriter, cancelled the issuance because the current market yield (5.36%) did not fall under the expected threshold for the cost of borrowing (4.75%) (<https://www.bloomberg.com/news/articles/2017-06-30/junk-bond-investor-unease-resurfaces-as-another-debt-deal-pulled>).

is consistent with a price support explanation. Section V discusses the time patterns of dealer inventory and profits and their implications for alternative explanations. Section VI concludes.

I. Data

Data Description Our main data set is the regulatory version of the Financial Industry Regulatory Authority (FINRA)’s Trade Reporting and Compliance Engine (TRACE) database of corporate bond transactions for 2005–2015. The data provide detailed information on all secondary corporate bond transactions. For each transaction, a dealer reports information such as trade execution date and time, trade price and quantity, a buy or sell indicator, the bond’s unique security identifier (the Committee on Uniform Security Identification Procedures number, or CUSIP for brevity), etc. Although the standard version of TRACE does not provide a reporting dealer’s identity or a counterparty’s identity, the regulatory version lets us identify the reporting dealer’s name and, if the counterparty is a dealer, the counterparty’s name as well.

The information on dealer identities is used to systematically match TRACE dealers with affiliated underwriters participating in bond issues. We obtain information about the lead underwriters of every firmly underwritten bond issue from the Mergent Fixed Income Securities Database (FISD). We deem dealer and underwriter to be affiliated if they are under the same holding company. For example, a dealer named “BANC OF AMERICA SEC” would be deemed affiliated with an underwriter called “BofA Merrill Lynch,” because their common parent is “BANK OF AMERICA, NATIONAL ASSOCIATION.” We link dealers and underwriters to their parent using bank holding company hierarchy structure information by the Federal Reserve System. This information is updated on a quarterly basis and made available via the Federal Financial Institutions Examination Council (FFIEC)’s National Information Center (NIC). The Federal Reserve assigns a unique identifying number, the Replication Server System Database Identifier (RSSD ID), for all financial institutions, main offices, and branches. First, we match TRACE dealer names and FISD underwriter names to an RSSD ID. Then, we mark dealers and underwriters as affiliated if, in a given quarter, their RSSD IDs can be mapped to the same ultimate holder.

We assign RSSD IDs to dealers and underwriters by comparing their reported names to their

Federal Reserve names. For dealers in TRACE, we use an approximate string matching algorithm to find the closest match, then manually check whether the resulting matches are correct.

Another data source is the National Association of Insurance Commissioners (NAIC). All U.S. insurers submit to the NAIC all bond transactions as part of their mandatory regulatory filings (Schedule D, Parts 3–5). The transaction data provide, among other things, transaction date, consideration, and a description. The description includes manually entered information about the type of transaction (“Maturity”, “Call @ 100.00”, etc.), or, if the transaction is a sale or purchase, about the counterparty (“JP Morgan Chase Securities”). For our analysis, we keep only actual buy and sell trades for which the counterparty is identifiable.⁶ As we did for the TRACE transaction data, we manually link each of these counterparties (e.g. “DEUTSCHE BANK SECURITIES, INC.” and “Deutsche Bank.”) to the RSSD ID of a dealer, to its ultimate holder, and finally to its affiliated FISD underwriters.

Event Selection Criteria In our empirical analysis, we investigate dealers’ trading behavior in a roughly year-long window centered around each new bond issuance *event*, starting five months before the event month and ending five months after it (eleven months). Our main focus is on existing bonds, i.e., other bonds by the same issuer which already exist as of the beginning of the event window. Thus, we structure our dataset so that each event is associated with all transactions of existing bonds that fall within the window. We also investigate transactions of the newly issued bond starting in the event month and ending five months after it.

In order to avoid overlap of event windows while keeping a reasonable sample size, we exclude events by a given issuer that are less than six months apart. For example, if a firm has issuance events on (1) January 10th of 2010, (2) February 10th of 2010, (3) March 10th of 2011, (4) and November 10th of 2011, we only consider events 3 and 4. Events 1 and 2 are too close and neither one should be included.

The choice of what events to include involves a trade-off. On one hand, avoiding overlap is important because we aim at studying dealer behavior in a given time window around the event. If the same *calendar* month appears in two events as a different *event* month, the measurement of dealer

⁶In a few cases, transactions are aggregated and the counterparty is indicated as “various” or similar term.

behavior may be biased. For instance, in our example, January 2010 is both month 0 of event 1 and month -1 of event 2. Thus, dealer behavior in January 2010 is likely neither the typical “month 0” behavior, nor the typical “month -1” behavior. On the other hand, strict avoidance of event window overlap would cause us to drop from the sample many issues of large, frequent issuers. We settle on a six-month distance between events as a compromise. Because the event window is 11 months wide (5 months on each side of month 0), a six-month distance guarantees that the event month (month 0) only appears in its own event window.

Multiple bonds issued on the same day are treated as one event, and dealers affiliated with any one of the bonds’ lead underwriters are deemed to be affiliated.

Bond Selection Criteria Within each event, we select bonds to be included according to the following criteria. First, bonds associated with an event must exist throughout the entire event window (i.e., must be outstanding at the beginning of the window and mature after the end). Second, to more sharply distinguish between trading of new bonds and trading of existing bonds, we further exclude bonds that were issued in the 12 months prior to the event date. Excluding bonds issued too recently is important because we aim at studying the behavior of dealers trading existing bonds. If the bond has been issued too recently, we risk measuring the behavior of dealers trading newly issued bonds instead. Since our event window is 11 months wide, we drop all bonds issued in the 12 months prior to the event date to avoid this confounding factor. Third, we exclude bonds that mature within 12 months of the event date to avoid any confounding factors related to the impending maturity. Finally, our final sample excludes bonds from financial sector firms, identified by the 1-digit SIC code “6”, to avoid cases in which dealers trade their own bonds and may have incentives that differ from the focus of our study.

The original FISD data contains 12,170 underwriting events with 3,834 distinct issuers. The sample selection criteria result in 4,834 underwriting events with 2,088 distinct issuers, 99 underwriters and 35,758 unique associated securities (both new and existing).

Dealer Selection Criteria In addition to the above criteria regarding events and their associated securities, our sample only includes the transactions of a subset of TRACE dealers. The main

purpose of our empirical analysis is to investigate differences in the trading behavior of affiliated dealers and unaffiliated dealers. In order to reduce the likelihood that our results are driven by unobservable systematic differences between underwriter-dealers and stand-alone bond dealers, we restrict our control group to consist of actual or potential underwriter-dealers. For example, for a bond offering underwritten by Goldman Sachs, we want to compare transactions by Goldman Sachs-affiliated dealers with those by Bank of America-affiliated dealers, but not with those by a small local dealer or a high-frequency trader. Thus, we include only trades from dealer-years (i, t) such that the parent firm of dealer i in year t is a lead underwriter (or the parent of a lead underwriter) for at least one event in year $t - 1$, t or $t + 1$. If there are unobserved characteristics that both cause a dealer to trade in a certain way, and make the dealer more likely to be an underwriter, then our final sample is less heterogeneous with respect to these characteristics.

Transaction Selection Criteria Dealers transact as principals, on their own account, or as agents, on behalf of clients. In the latter case, dealers do not have freedom with regard to the price they will bid or offer because they merely execute client orders. Accordingly, we exclude agent trades from most of our analyses. The only exception is our market-making profit measure, which includes agent trades and the commissions earned thereupon.⁷ The rationale for including agent trades is that an increase in the volume of commission-earning agent trades is a valid source of market-making profits.

Summary Statistics Table I provides summary statistics about transactions data included in the final sample. The numbers for the leftmost columns for Total Number of Dealers and Total Volume are calculated from the entire TRACE database. Annual aggregate trade volume ranges from \$5.8 trillion to 10.6 trillion, with 1,042–1,587 distinct dealers active in any given year. Table I shows that our final sample accounts for 13.7% of the total volume in the entire data, with the number of active dealers reduced to 107 (66–79 in any given year). Of these, 52 are affiliated with at least an underwriting event (26–39 in any given year), and trades by affiliated dealers make up 43.5% of the total volume in the sample (30–50% in any given year).

⁷Dealers earn zero spread on the typical sequence of agent trades, but they are allowed to charge a commission. Dealers are required to report a commission to TRACE whenever they receive a positive commission amount.

[Insert Table I here]

Sample Structure Our unit of analysis is a Dealer-Bond-Week. Our sample is structured around event time, not calendar time. Thus, a “week” is not identified in calendar time (e.g., week 13 of year 2010) but rather relative to the event date (e.g., week -12 of event 131). We break our transaction-level sample into four subsamples by trade side (Buy/Sell) and counterparty type (Dealer/Client). Using the four subsamples, for each dealer-bond we calculate four weekly time series of volume-weighted average transaction prices. Having a time series of Dealer-Bond-level observations permits us to carry out our main analysis, in which we compare the transaction prices of the same bond for affiliated and unaffiliated dealers.

In order to avoid the effect of accrued coupon within a week, we use the clean price of bonds in our analyses. It is worth noting that the clean price itself is not entirely immune from accruals. For instance, the clean price of a 5-year bond trading at 90 percent of face value increases by roughly 2 basis points between a Monday and the subsequent Friday. However, this would only bias our results if affiliated dealers and unaffiliated dealers tend to trade on different weekdays. In unreported tabulations, we did not uncover any difference in the weekday pattern of trading by affiliated and unaffiliated dealers. This is not surprising, because they are largely the same dealers swapping roles from one event to the next.⁸

Finally, pooling all transactions (as opposed to the four subsamples separately), we also calculate dealer-bond-level measures of weekly profits, and dealer-level measures of weekly estimated inventories and of monthly dealer centrality. The construction of these variables is explained when they are first introduced.

⁸In theory, one potential solution would be to translate clean prices into yields. Nonetheless, we prefer prices for two reasons. First, we find the resulting coefficients easier to interpret. Second, while the price is directly observable, the yield is not. Transforming the price into a yield would require perfect knowledge of maturity, coupon, compounding frequency, type of coupon (fixed or variable), and any conversion and redemption options embedded in the bond). Thus, in practice, the noise added by translating prices into yields dwarfs the precision gained by eliminating small intra-week discrepancies that in addition do not show any systematic differences between affiliated and unaffiliated dealers.

II. Transaction Prices

A. Dealer activity around events

We begin by showing evidence of abnormal trading activity for an issuer’s existing bonds around the issue of a new bond. Figure 1 shows that the trading volume of both affiliated dealers (solid line) and unaffiliated dealers (dashed line) spikes in the weeks around week 0 (the issue week). This spike is followed by an “off the run” effect: after the event, trading volume drops noticeably below the pre-event level. This is true for both affiliated and unaffiliated dealers. This effect may reduce the precision of our estimates in the rest of the section for the months following the issue event.

[Insert Figure 1 here]

The figure also shows that affiliated dealers’ volume of client-facing trades increases dramatically, roughly twice as much as the increase in their unaffiliated counterparts’. On the other hand, dealer-to-dealer volume spikes asymmetrically. Affiliated dealers sell relatively more to other dealers, while unaffiliated dealers buy relatively more from other dealers.

Taken together, these patterns are consistent with a “car dealership” explanation of the underwriter-dealer’s role: when a customer buys a new car from a dealer, the dealer offers to trade in the old car regardless of where it was originally bought. As affiliated dealers sell the new bonds, it is likely that many clients also want to get rid of the issuer’s existing bonds (e.g., to rebalance, or because they are only interested in “on-the-run” bonds). Thus, overall the evidence suggests that affiliated dealers collect a large amount of inventory from clients. Some of it is disposed of by selling to other clients, and the rest via inter-dealer trades.

B. Empirical design

In our main analysis, we investigate differences in the time pattern of transaction prices of affiliated and unaffiliated dealers around bond issuance events. To do so, we use a 44-week window centered on the issue week. We divide the event window into eleven 4-week “months”, covering weeks from $[-20, -17]$ to $[+20, +23]$. We then estimate the following dynamic difference-in-differences specification: for dealer i trading bond j in week w from the time of a new event k (i.e. issuance of new bond k

by the issuer of bond j),

$$\text{Price}_{ijkw} = \sum_{m=-4}^5 (\alpha_m + \beta_m \cdot A_{ik}) \cdot \mathbf{1}[\text{Month}_{kw} = m] + \xi_{ijk} + \xi_{t(k,w)} + \varepsilon_{ijkw}. \quad (1)$$

Variable A_{ik} is a dummy variable that is equal to 1 if dealer i is affiliated with one of the lead underwriters of issuance event k . We interact A_{ik} with $\mathbf{1}[\text{Month}_{kw} = m]$, an indicator variable that is equal to 1 if the current week w of event k falls within the m -th month. All effects are estimated relative to month -5, the omitted category. We call this specification “dynamic” because we estimate the effect of interest for multiple months, and not simply for the pre-event and post-event periods. In this specification, the main coefficients of our interest are β_m ($m \in \{-5, \dots, 6\}$), which capture the pricing difference between an affiliated and unaffiliated dealer prices for bond j in month m .

The granularity of our data allows us, through the use of fixed effects, to control for observable and unobservable heterogeneity across dealers, bond, issuers, and calendar time. The specification has two sets of fixed effects. The ξ_{ijk} term refers to fixed effects for each combination of Event \times Dealer \times Bond, and it enables us to focus on differences between affiliated and unaffiliated dealers in the time pattern of pricing, within each event, on a bond-by-bond basis.⁹ The $\xi_{t(k,w)}$ term refers to fixed effects for the *calendar* week corresponding to week w of event k , and it controls for common effects shared by events that happen at the same calendar time.

Our difference-in-differences approach addresses an important objection: likely, issuers do not issue at random times. Conditional on having outstanding bonds, a firm would want to issue at times when these outstanding bonds have attractive valuations. Thus, the price of bonds is likely to peak at or around the event time. However, this endogenous timing effect cannot explain a difference in the prices paid by different dealers at the same time.

Because Equation (1) is estimated using Event \times Dealer \times Bond fixed effects, our finding is also robust to a number of alternative explanations. For instance, a positive “buy price” coefficient may not simply reflect the fact that affiliated dealers purchase higher-priced bonds relatively more

⁹By “Event \times Dealer \times Bond” fixed effects we mean that the regression is specified with an indicator variable for each unique combination of event (9-digit CUSIP of the bond being issued), dealer (RSSD ID of the ultimate holding company), and bond (9-digit CUSIP of the existing bond by the same issuer).

often for some reasons (e.g., the bonds have better liquidity). If that were the case, the higher price level would be absorbed by the bond component of the fixed effects. Similarly, it is possible that affiliated dealers may differ from unaffiliated dealers as a whole (e.g., they may be larger or more central to the dealer network), and this somehow causes them to pay unconditionally a higher price to other dealers for all buy transactions around an issuance event. However, this explanation cannot drive our finding because the dealer component of the fixed effects would absorb systematic differences in the price level, as well as other bias due to dealer heterogeneity, both within and across affiliated and unaffiliated dealers. Moreover, our sample selection criteria already limit potential heterogeneity in dealers' underwriting capabilities.

As an important caveat, our regression shows that affiliated dealers pay higher prices for bonds around an issuance event, but no amount of fixed effects can show that affiliated dealers behave differently *because* of the event itself. For instance, it could be that there is some unobservable difference between affiliated dealers and unaffiliated dealers that causes affiliated dealers to act differently around bond issues. To establish causality, we would like to study a laboratory experiment in which dealers are randomly assigned to issues. Unfortunately, this is not possible; as a second-best, however, our data selection procedure largely mitigates this concern by selecting a control group of unaffiliated dealers that starkly resembles the treatment group of affiliated dealers. In fact, we often observe near-simultaneous issue events led by different underwriters, and therefore our treatment group and control group consist of the same few firms that swap places from event to event.

C. Monthly dynamic pattern

The estimation results of Equation (1) are reported in Table II. Each column reports the results of a regression estimated using one of our four subsamples by trade side and counterparty type (Buy from Dealer; Buy from Client; Sell to Dealer; Sell to Client). Each coefficient measures the difference between the transaction price of affiliated and unaffiliated dealers in month m relative to their respective levels in month -5 .

[Insert Table II here]

The coefficient is expressed in percent of face value. For instance, in Column (1), a coefficient of 0.16 for month -1 means that affiliated dealers paid on average 16 cents per \$100 face value (or 16 basis points) more than unaffiliated dealers when buying bonds from other dealers. The coefficient magnitude is large. For instance, it is of the same order of magnitude as many recent estimates of average round-trip costs (15-35 bps; Bessembinder et al., 2018; Choi and Huh, 2016; Goldstein and Hotchkiss, 2018). This aggressive bidding behavior becomes statistically detectable in the month before the issue event—a timing roughly consistent with the reception of the underwriting mandate. The pattern continues after the event, peaking at around month 4, and weakens around five months after the issuance.

The baseline coefficients α_m (the coefficients on the month indicator variables) are also interesting. They show a meaningful unconditional increase in prices (roughly 20 basis points) in the two months after the issue. We interpret this finding as evidence of a positive market reaction to a successful issue, a positive signal that the firm is still creditworthy. Moreover, to the extent that the new issue is subordinated to the existing bonds (because the latter are senior, or are due sooner), the cash infusion directly affects the value of these existing obligations by increasing the likelihood that they will be paid. This finding further demonstrates the value of a difference-in-difference approach to disentangle the effect of interest from the many other endogenous influences that affect the price of existing bonds around a new issue.

Column (2) shows the buy price difference in client-facing trades. It indicates that the aggressive bidding becomes significant at much later time (three month after the issuance) with smaller magnitude relative to inter-dealer buy trades. Column (3) shows the same coefficients using the sample of sell transactions where the counterparty is a dealer, while Columns (4) shows the same coefficients using samples of buy and sell transactions where the counterparty is a client.

All columns show a similar time pattern, with the price difference between affiliated and unaffiliated increasing over time. However, in Columns (2)–(4), there is no evidence of pre-issuance action (no coefficients are statistically significant during the pre-issuance period), and the magnitude of coefficients is smaller. Comparison of Columns (3) and (4) reveals that, during the post-issuance period, affiliated dealers sell bonds at a higher price to clients but not to other dealers.

Taken together, Columns (1)–(4) suggest that affiliated dealers provide cross-security price support for the issuer’s existing bonds before the new bond is issued, as they buy at high prices but do not sell at proportionally high prices. The fact that pre-issuance price support appears to be provided only with respect to dealer-facing trades may appear puzzling. However, we find that the volume of client-facing buy transactions (1.5 percent of the new bond’s issue size) is roughly 10 times larger than its dealer-facing equivalent (0.15 percent). This volume difference suggests that it may be less costly to support prices via inter-dealer rather than client-facing purchases.

Even after issue events, the cross-security price support continues. In general, we find that inter-dealer purchases are the main means for the operation. Supporting prices via inter-dealer purchases may also be more effective. Unless the issuing firm uses the proceeds from the new bond to retire another bond, the supply of its bonds increases, and with it, all dealers’ inventory exposure to that firm. Since unaffiliated dealers have no commitment to provide price support, they may reduce their exposure by selling existing bonds, putting pressure on their price. Aggressive bidding sets a high floor to the value of existing bonds and works as an incentive for unaffiliated dealers not to sell off their inventory.

Our result shows that underwriters’ price support for the new security entails more complex dimensions than those documented in prior literature: it may start before the new security is issued, and it may involve securities other than the new one.

III. Maturity and Liquidity

It is natural to ask which bonds underwriter-dealers target to implement their price support strategies when there are multiple bonds from an issuing firm. To study this question, we segment bonds with respect to two relevant dimensions: maturity and liquidity.

Once identified the relevant subset of bonds, we estimate the following regression specification:

$$\text{Price}_{ijkw} = \sum_{m=-4}^5 (\alpha_m + \beta_m \cdot A_{ik} + \gamma_m \cdot A_{ik} \cdot B_{jk}) \cdot \mathbf{1}[\text{Month}_{kw} = m] + \xi_{ijk} + \xi_{t(k,w)} + \varepsilon_{ijkw}. \quad (2)$$

All variable definitions are consistent with the ones in Equation (1), except for the indicator variable

B_{jk} . The exact definition is given case by case below, but in general B_{jk} is 1 if existing bond j belongs to the relevant subset (i.e., if we expect bond j to be more likely to be targeted by the underwriter of event k) and 0 otherwise.

The main goal of our analyses using triple difference terms is to show that affiliated dealers focus on a specific set of bonds for their price maneuvers. Thus, the γ_m 's on the triple difference terms are our coefficients of interest as they measure differences in affiliated dealers' aggressive bidding behavior across different sets of existing bonds. For the same reason, we omit the α_m coefficient estimates in our tables.

A. Maturity

When potential buyers of new bonds seek a reference point to price a new issue, they are likely to rely on the price of a bond with similar maturity, because the term structure of interest rate is generally not flat.

In order to formally test this hypothesis, we identify a subset of existing bonds whose maturity is similar to the new bond's maturity and estimate Equation (2). In this case, B_{jk} equals 1 when bond j 's remaining maturity is within 2 years of the new issue k . In order to focus on those issuers that have enough preexisting bonds to provide underwriters with a meaningful choice, we restrict our sample to events for which there are both existing bonds of similar maturity and existing bonds of dissimilar maturity.

Table III presents the results. The magnitude of the aggressive bidding activity is much larger in this subsample than in the unconditional case of Table II. In our baseline results, during the month leading to the issue, affiliated dealers pay 16 basis points for the same bond at the same time relative to unaffiliated dealers. When we consider only such bonds, in month -1, affiliated dealers bid 33 basis points higher for these bonds relative to unaffiliated dealers. In fact, most aggressive bidding in inter-dealer trades appears to be concentrated in bonds with similar maturity: once an interaction term for these bonds is included, the coefficient for the remaining bonds is not significant prior to the issue events. Aggressive bidding on bonds of dissimilar maturity appears only in the post-event period. This result implies that affiliated dealers focus on similar-maturity bonds in

their pre-issuance price maneuvers.

[Insert Table III here]

B. Liquidity

Generally, bond liquidity exhibits substantial cross-sectional variation, even within bonds issued by the same firm. This heterogeneity is driven by differences in bond-specific attributes such as initial issue size or complex embedded options, but also by on-the-run/off-the-run phenomena such as the one prevailing in the U.S. Treasury market.

Although in this paper we do not attempt to investigate the main drivers of heterogeneity in liquidity in the corporate bond market, the existence of heterogeneity creates an opportunity for a sharper test of our hypothesis. From the perspective of a dealer, the liquidity of existing bonds imposes important constraints on the feasibility of price maneuver operations. From the perspective of a potential investor, the price of a relatively liquid bond is more credible as a reference price for the new issue than a bond with only a few trade marks. Thus, we expect liquid bonds to be disproportionately targeted by underwriter-dealers.

In order to formally test this hypothesis, we identify a subset of “liquid” bonds and estimate Equation (2). We proxy for liquidity by using trading volume in the 3 months starting 4 months prior and until 1 month prior to the issuance event. Specifically, B_{jk} equals 1 when bond j 's volume is in the top quartile of all existing bonds for the new issue k . In order to focus on those issuers that have enough preexisting bonds to provide underwriters with a meaningful choice, we restrict our sample to events for which there are both liquid and illiquid existing bonds.

Table IV presents the results. When bonds are classified as liquid, the magnitude of aggressive bidding before the issue is larger relative to the unconditional case of Table II. In our baseline results, during the month leading to the issue affiliated dealers pay on average 16 basis points more for the same bond at the same time relative to unaffiliated dealers. The results from Column (1) show that most aggressive bidding in inter-dealer trades appears to be concentrated in liquid bonds. When we consider only such bonds, affiliated dealers pay 37 basis points higher for the same bond relative to unaffiliated dealers, and the coefficient on the other bonds becomes insignificant.

[Insert Table IV here]

The results in this section suggest that affiliated dealers select a particular set of existing bonds to implement their strategies. The selection criteria appears to be consistent with the explanation that the aggressive bidding by affiliated dealers is driven by an incentive to create a price reference for investors, in favor of the underwriter’s client.

IV. Dealers’ Incentives

In this section, we consider several testable implications to further verify the cross-security price support mechanism. Bidding an abnormally high price for bonds is costly, but we do not find evidence that affiliated dealers finance this operation by selling bonds to their clients for a higher price than unaffiliated dealers. This result suggests that the aggressive bidding must be related to dealer-underwriters’ incentive to cater to bond issuers.

Underwriters’ incentives may involve two different channels. First, it is common for a prospective issuer to cancel the deal if the marketable bond yield does not fall under a certain desirable threshold. In this case, to avoid the loss of fees that comes with a canceled deal, the underwriter would have an incentive to try to lower the reference yield for the new bond prior to the scheduled issuance date.

Alternatively, even if the deal is guaranteed to proceed, underwriters’ reputation is important for future business. Because there is a finite number of underwriters and issuers in reality, underwriter-issuer matching is a repeated game. Ljungqvist et al. (2006) find that prior underwriting track record is the main determinant of winning the underwriting mandate. Although they do not attempt to pin down one specific channel for the incentive, their results suggest that underwriters and their affiliates have an incentive to engage in a potentially costly price support operation with or without any particular clause in the underwriting contract.¹⁰ In the following subsections, we investigate two circumstances that affect the underwriter’s incentives.

For the purposes of this section, we classify events as “important” based on the issuer’s character-

¹⁰Nagler and Ottonello (2018) also show that underwriters systematically place bonds to relationship investors.

istics and estimate the following regression specification:

$$\text{Price}_{ijkw} = \sum_{m=-4}^5 (\alpha_m + \beta_m \cdot A_{ik} + \gamma_m \cdot A_{ik} \cdot E_k) \cdot \mathbf{1}[\text{Month}_{kw} = m] + \xi_{ijk} + \xi_{t(k,w)} + \varepsilon_{ijkw}. \quad (3)$$

All variable definitions are consistent with the ones in Equation (1), except for the indicator variable E_k . The exact definition is given case by case below, but in general E_{jk} is 1 if event k is important (i.e., if we expect the underwriter to exercise above-average care) and 0 otherwise.

Our main goal here is to show that affiliated dealers’ incentive to engage in price maneuvers varies across events based on issuer characteristics. Thus, the γ_m ’s on the triple difference term are our coefficients of interest as they measure differences in affiliated dealers’ aggressive bidding behavior across different events. For the same reason, we omit the α_m coefficient estimates in our tables.

A. *Underwriter-issuer relationships*

Underwriters’ commitment to supporting the price of existing bond issues for large-volume issues may be incentivized by the value of relationship with bond issuers. If this is the case, we should observe that “important” clients get a favorable treatment.

We use two measures of past issuance activity as a proxy for the value of client relationships: past number of issues (frequent issuer) and past volume of issuance (large issuer). We measure frequency as the total number of issuance events by that issuer in the past 3 years, and volume as the total dollar amount issued by that issuer in the past 3 years. We then use these measures to rank issuers by past issuance frequency within every calendar month.

To investigate whether the aggressive bidding pattern is more pronounced when the bond issuers are likely to be valuable clients to underwriters, we identify two subsamples of interest. The first subsample corresponds to the top quartile of issuers by past issuance frequency, and the second subsample corresponds to the top quartile of issuers by past issuance volume. We estimate Equation (3) on these subsamples. The results are reported in Tables V (frequency of issues) and VI (volume of issuance).

The results appear to confirm the relationship hypothesis. Column (1) of both tables mirrors our

overall result for inter-dealer buy trades. In Table V, when we define valuable clients by past issue frequency, the magnitude of the coefficients on the interaction terms is noticeably larger than in our baseline estimates: for these bond issuers, we observe an inter-dealer buy price difference of between 0.19% and 0.38%, peaking a month prior to the event, while the baseline coefficients are small and insignificant. Thus, most of the aggressive bidding seems to be concentrated on the issues by important clients.

Moreover, Columns (2) and (3) of the same tables indicate that affiliated dealers also buy from clients and sell to other dealers at a significantly higher price. These results contrast with the ones from our overall sample, in which the price support pattern is much stronger in inter-dealer trades. This difference suggests that affiliated dealers cater to frequent issuers by paying a higher price in large client-facing trades.

While generally transaction prices of affiliated dealers are reliably positive and significant in the “Buy from Dealer” sample, in Tables V and VI the triple interaction coefficients (Month = $m \times$ Affiliate = 1 \times Subsample = 1) are also positive and significant in the “Sell to Dealer” sample, and for certain months even higher. However, once summed to the baseline interaction coefficients reported in the upper part of the table (Month = $m \times$ Affiliate = 1), the total effect is lower.

[Insert Tables V and VI here]

B. Summary of findings

Figure 2 summarizes our estimation results for affiliated dealers’ buy trades, which appear to be the main type of transaction on which dealers’ price maneuvers are concentrated. For our baseline results, we plot the coefficients on the interaction terms (Month = $m \times$ Affiliate = 1) from Equation (1). These are represented by the solid line, corresponding to Column (1) of Table II.

For our results by bond or issuer characteristics, we plot the sum of the coefficients on the triple interaction terms (Month = $m \times$ Affiliate = 1 \times Subsample = 1) and the baseline interaction terms (Month = $m \times$ Affiliate = 1) from Equations (2) and (3). These are represented by the dotted lines with different markers, corresponding to Columns (1) of Tables III–VI. The affiliated dealers’ bid prices become significantly higher than unaffiliated ones, starting immediately prior to the issue

event.

[Insert Figure 2 here]

In sum, we find compelling evidence that affiliated dealers aggressively bid for existing bonds of the issuer of the new bond by paying a higher price relative to unaffiliated dealers. Such behavior is most pronounced and robust in inter-dealer trades. Our analysis supports the hypothesis that cross-security price support is focused on bonds that are more relevant as price benchmarks, and motivated by how important the issuer is to the underwriter.

V. Inventory and Profits

In the previous section, we have presented evidence consistent with dealers providing price support before and after an issue event. In this section, we turn our attention to other plausible reasons why affiliated dealers would exhibit atypical trade behavior. For instance, dealers' use of existing bonds as a hedging instrument may also explain the observed aggressive bidding pattern. If this explanation is correct, there would be testable implications for dealers' inventories. Similarly, aggressive bidding could be part of a self-interested trading strategy. If this explanation is correct, any benefits dealers obtain from such a strategy would be reflected in their profits. To examine these possibilities, we estimate the basic specification in Equation (1) using inventory and profits as the dependent variables, in order to examine whether the time pattern of these variables is consistent with any alternative explanations.

A. *Short covering and hedging*

One possibility could be that the aggressive bidding pattern is evidence of the dealer covering short positions it entered previously. Short positions could exist for multiple reasons.

First, as part of a bond offering, underwriters typically commit to making a market for the new bonds. In Appendix B we show an excerpt from an offering prospectus stating that the underwriters "intend to make a market in the notes of each series" after the offering's completion. This liquidity provision role requires the underwriter and its affiliated dealer to initially hold a large positive

inventory of the new bonds, then to gradually unwind the position. By taking on inventory, the dealer becomes exposed to the credit risk of the issuer. One way to mitigate this risk would be to establish a short position in the issuer’s existing bonds. If the prices of new and old bonds are highly correlated, any loss on the inventory would be largely offset by gains on the short position.¹¹

In the excerpt in Appendix B, the underwriters also refer to the possibility of short-selling “any series” of the issuer’s bonds in the open market, adding that “the underwriters’ purchases to cover their short sales may have the effect of raising or maintaining the market price of the notes of the applicable series or preventing or retarding a decline in the market price of such notes.” Thus, short positions may be opened and covered as a tool to directly support the price of the issuer’s bonds.

Although these explanations are not necessarily able to fully explain our main finding, we directly test whether affiliated dealers take on significant negative inventory of existing bonds. To this end, we estimate the same specification of Equation (1), this time with inventory as the dependent variable:

$$\text{Inventory}_{ikw} = \sum_{m=-4}^5 (\alpha_m + \beta_m \cdot A_{ik}) \cdot \mathbf{1}[\text{Month}_{kw} = m] + \xi_{ik} + \xi_{t(k,w)} + \varepsilon_{ikw}. \quad (4)$$

We construct our measure of inventory in both dollar and relative terms as follows. First, for a given dealer and existing bond, we assume that the initial inventory is zero at the beginning of our sample, and we use transaction data to keep track of inventory at any subsequent point in time. We use this constructed inventory measure because our data contains information about transactions (flow), but not about true inventories (stock).¹² However, this measure captures the time pattern of inventory equally well, and therefore we deem it suitable for our purposes.

Next, for a given dealer and event week, we obtain our dollar inventory measure by aggregating the end-of-week inventory value of all existing bonds by the event’s issuer. Aggregating inventory at the issuer level is necessary because the hedging motive is well defined only at the whole-portfolio

¹¹For the typical equity issuer with only one class of equity securities, this mechanism is not available to the underwriters. Moreover, in the presence of multiple classes of stocks, it is usually impractical to short-sell stock of classes other than the one being issued.

¹²Given the lack of information, inventory level (stock) cannot be recovered for the bonds that existed before the beginning of our sample. Nevertheless, for various reasons it is impractical to reconstruct absolute inventory even for bonds that we observe from the start. One of these reasons is that the reporting of primary market trades in TRACE is unreliable, at least in the first half of our sample.

level (as opposed to the individual bond level). Consequently, for this specification, our dependent variable is dealer-specific (indexed by ikw) rather than dealer-bond-specific (indexed by $ijkw$), and one observation consists of a Dealer-Event-Week.

Finally, we define our relative inventory measure as dollar inventory divided by new issue size. Expressing inventory relative to the new issue size adjusts for the great size variation that is characteristic of bond issues in a way that is consistent with the hedging motive, as clearly a large issue would require a larger short position to hedge, other things being equal.

The results using the relative inventory measure are reported in Column (1) of Table VII. The estimates show no evidence that affiliated dealers establish a negative inventory on existing bonds. Instead, the coefficients on the baseline month indicator variables show statistically significant evidence that all dealers increase their inventory (i.e., provide liquidity) starting in the issue month and continuing until the end of the event window. The average unaffiliated dealer’s inventory increases by 0.028% of new issue size in the event month, with affiliated increasing by an additional 0.169%, or 0.197% in total.¹³ These findings suggest that affiliated dealers buy a large volume of bonds from clients in the event month, consistent with the evidence for a “car dealership” role of affiliated dealers that we previously showed in Figure 1 (Section II.A). These findings also directly verify that affiliated dealers’ aggressive bidding pattern is not driven by a hedging or short-covering motive.

We also report results using a dollar measure of inventory in Column (4) of Table VII. The dollar measure places more emphasis on large issues and better captures the dealer’s capital commitment. Our dollar results show that unaffiliated dealers take on an average inventory of existing bonds of \$292,200 in the event month, and declining thereafter. Affiliated dealers commit an additional \$966,700 in the event month. Both in dollars and in percent, the excess inventory is large and long-lived: although it declines over time, both affiliated and unaffiliated dealers still hold economically meaningful inventory in month 5. These results are further evidence against the hedging motive.

[Insert Table VII here]

¹³The average issue size in our sample is roughly \$900 million.

B. Trading profits

In this subsection, we consider the alternative possibility that the aggressive bidding pattern is driven by the pursuit of profit opportunities created by the underwriting mandate. In this case, a dealer would bid aggressively to build a long position in the existing bonds, under the expectation that it can sell the bonds at a profit in subsequent periods. We identify two different underlying mechanisms.

The first mechanism is that the issuance event may boost the dealer's market-making activities. Ellis et al. (2000) find that dealers tend to become a dominant market-maker for the security offered by their affiliated underwriter. This phenomenon is also visible in our data. Figure 3 shows that the average unaffiliated dealer takes up 2.5 percent of weekly transaction volume in the 6 months after a new bond is issued. In the same period, the average affiliated dealer transacts a 3 to 6 times larger volume (7 to 18 percent). Notably, the affiliated dealer's market share peaks immediately after issuance. This result indicates that dealers' and underwriters' incentive is well aligned.

[Insert Figure 3 here]

If this dominance extends to the existing bonds by the same issuer, it could explain the aggressive trading pattern we observe. Li and Schürhoff (2018) show that in the municipal bond market more central dealers capture higher spreads. If issuance events are to have a positive effect on the dealer's profits, they should do so by increasing the dealer's centrality.

In Section II.A, we already showed that trading volume of existing bonds peaks in the issue month, and the peak is much higher for affiliated dealers. Thus, by virtue of its central position in the dealer network, an affiliated dealer may be able to charge a premium ask price when selling bonds. In that case, up to a point, the dealer would find it profitable to also buy at a higher bid price. This mechanism can explain aggressive bidding in the pre-issuance period as well, as the dealer already knows it will gain a central position afterwards.

Here we test this hypothesis directly by estimating the same specification of Equation (1) using

standard measures of dealer network centrality as the dependent variable:

$$\text{Centrality}_{ijkt} = \sum_{m=-4}^5 (\alpha_m + \beta_m \cdot A_{ik}) \cdot \mathbf{1}[\text{Month}_{kt} = m] + \xi_{ijk} + \xi_{t(k,m)} + \varepsilon_{ijkt}, \quad (5)$$

where Centrality_{ijkt} is one of four measures summarily described in the caption to Table VIII. Li and Schürhoff (2018) provide a detailed definition and interpretation of each measure.

Because this equation is estimated on a monthly-frequency panel, time is indicated by t , instead of the usual w . This coarser level of aggregation is necessary because there are not enough observations at weekly frequency to calculate the centrality measures. Table VIII shows the estimates of Equation (5). The table shows an increase in centrality in month 0, suggesting that the dealer’s status as a market-maker of existing securities does receive a boost from the issuance event, albeit a short-lived one. This result is also consistent with our volume and inventory results (Figure 1).

[Insert Table VIII here]

The second mechanism is that underwriters acquire material nonpublic information about the issuer during the due diligence process, or in general because of their privileged access to management. If a dealer acquires positive information on the issuer from an affiliated underwriter, it may be willing to pay a premium to build a position before the information becomes public at the time of issuance in order to profit from the informational advantage. At least for the pre-issue period, this mechanism would explain our finding of aggressive bidding.

Both hypotheses have implications for dealers’ profits. The first hypothesis implies that market-making profits of affiliated dealers should rise around an issuance event, whereas the second hypothesis implies that profits from information-driven position taking (position-taking profits) should increase after the event when the bond prices start reflecting the private information. Accordingly, we construct a measure of total dealer profit directly from trade marks, and we decompose it into these two components based on a time threshold: positions that were built and unwound within 7 calendar days are considered market making, and other positions are considered speculative (i.e., positions taken with the intent of profiting from an informational advantage).¹⁴

¹⁴The 7-day threshold is somewhat arbitrary. For robustness, we also calculate market-making return using 5-, 10-, and 15-day thresholds to identify market-making activity with essentially identical results (see Table A.II in Appendix A).

As an example, consider the following transactions: a dealer makes a large initial purchase of 3,000 units of a given security in week 0. Then, over weeks 2–3, the dealer sells 1,000 units of inventory. In week 4, the dealer purchases 500 units of inventory and shortly after sells 700 units. Finally, in weeks 5–10 the dealer gradually sells the rest of the inventory. Our interpretation of these transactions is that by buying 3,000 units of the bond the dealer has taken a position, becoming exposed to the credit risk of the issuer. Profits resulting from gradually unwinding the position should be counted as position-taking profits because the dealer takes inventory risk, i.e., buys the bonds expecting to sell them for a higher price at some unspecified point in the future. However, the gradual unwinding that takes place in weeks 1–10 is briefly interrupted by a bout of market-making in week 4: the dealer has made a quick round-trip transaction, buying 500 units and quickly selling them with little or no exposure to credit risk. The profits from selling the first 500 out of 700 units should therefore be counted as market-making profits, and the rest as position-taking profits because they are simply a continuation of the gradual unwinding.

To test our alternative hypotheses, we estimate two separate specifications in which dealer outcomes are measured as dollar profits and returns, respectively. Dollar profits are calculated for every transaction that closes a position using the LIFO method of accounting, which naturally reflects our interpretation of the above transactions. Market-making profits also include commissions on agent trades, and position-taking profits also include unrealized gains on inventory. Returns are calculated by dividing dollar profits by an appropriately defined measure of committed capital. A detailed description of our procedures to calculate dollar profits and returns is given in Appendix A.

Because the return measures are defined at the transaction level, they allow us to compare the profitability of single transactions done by dealers of different sizes. Thus, we aggregate transactions into Dealer-Bond-Week observations as in most of our specifications. The specification we estimate is

$$\text{PT or MM Return}_{ijkw} = \sum_{m=-4}^5 (\alpha_m + \beta_m \cdot A_{ik}) \cdot \mathbf{1}[\text{Month}_{kw} = m] + \xi_{ijk} + \xi_{t(k,w)} + \varepsilon_{ijkw}. \quad (6)$$

In contrast, the dollar measures can be aggregated at Dealer-Week level and they better represent

the total profitability of an event for the average dealer. In particular, the market-making *return* measure indicates the profitability of the average dollar of volume traded, and therefore does not reward a dealer for increased volume at constant spread, whereas the *dollar* measure does. The specification we estimate is

$$\text{PT or MM \$ Profit}_{ikw} = \sum_{m=-4}^5 (\alpha_m + \beta_m \cdot A_{ik}) \cdot \mathbf{1}[\text{Month}_{kw} = m] + \xi_{ik} + \xi_{t(k,w)} + \varepsilon_{ikw}. \quad (7)$$

Columns (2)–(3) of Table VII report the estimates of Equation (6) using market-making returns and position-taking returns, respectively. Returns are essentially constant over the event time window. For short-term market-making activities, the difference between affiliated and unaffiliated dealers is close to zero and not significant, except for month 0 (the issue month) in which it drops to negative 4 basis points (presumably the cost of retiring the customers’ old bonds, as discussed in Section II.A). As for long-term position-taking activities, the coefficient is positive and statistically significant in month 0 (10 basis point/week), consistent with a liquidity provision explanation.

Columns (5)–(6) of Table VII report the estimates of Equation (7) using market-making and position-taking dollar profits, respectively. The table shows qualitatively the same findings as Columns (2)–(3), but with two differences. First, market-making profits are still tiny in magnitude (\$200 per week per bond), but they are now significantly positive in the event month and significantly negative thereafter. Taken together with Column (2), these results suggest that in the event month affiliated dealers manage to trade a higher volume at lower spread, with a positive overall effect on market-making profits. Second, position-taking profits of affiliated dealers are not statistically different from those of unaffiliated dealers, they do not show any clear pattern throughout the window, and in particular they are not higher in the post-event period.

Thus, at least for preexisting securities of the same issuer, affiliated dealers do not seem to be at an advantage. The increase in affiliated dealer centrality that we uncover explains the finding of increased market-making profits in month 0, but it does not explain our finding of aggressive bidding in the subsequent months, and certainly not in the month before the event. Also, the absence of a jump or increasing pattern over time in position-taking profits implies that information-driven trading of pre-existing bonds is not an economically meaningful benefit of the underwriting

mandate, or at least it is not the main driver of aggressive bidding.

C. Client access

One could conjecture that affiliated dealers may have access to “better” clients, i.e., clients that bring either a large volume of business or more favorable business. Because our sample only includes dealers with underwriting capacity, affiliated dealers cannot have access to a better client list unconditionally. However, it is possible that upon an event affiliated dealers gain increased access to better clients limited to the trades of existing bonds. In this case, affiliated dealers may exhibit aggressive bidding under the expectation that access to those clients would allow them to sell the bonds more easily. In this subsection, we examine if the evidence supports this conjecture, i.e., if affiliated dealers actually have better access to important bond investors.

For this task, we use U.S. insurance company transaction data from the National Association of Insurance Commissioners (NAIC). As we did for the TRACE transaction data, we manually link the reported counterparties to their affiliated FISD underwriters. Since insurance companies are the largest class of corporate bond investors in U.S., we believe that this smaller sample is reasonably representative of the universe.

We first define important clients by their past share of bond transactions. Specifically, we classify a client as a Top 10% client for every issue event in year t if the insurance company falls in the top 10 percentile by transaction volume using all bonds during year $t-1$. We repeat this classification using 25 and 50 percentile thresholds to define Top 25% and Top 50%/Bottom 50% clients respectively.

To uncover any differences in client access, we estimate the same specification of Equation (1) using the number of clients in each classification as dependent variable:

$$\text{No. of Clients}_{ikw}^q = \sum_{m=-4}^5 (\alpha_m + \beta_m \cdot A_{ik}) \cdot \mathbf{1}[\text{Month}_{kw} = m] + \xi_{ik} + \xi_{t(k,w)} + \varepsilon_{ikw}, \quad (8)$$

where $\text{No. of Clients}_{ikw}^q$ is the number of clients classified as group q ($q \in \{\text{All}, \text{Bottom 50\%}, \text{Top 50\%}, \text{Top 25\%}, \text{Top 10\%}\}$) for dealer i of issue event k at week w .

Table IX reports the regression results. Each column of the table corresponds to the number of

clients in a different group. The findings are consistent across all columns. All dealers' interactions with insurance companies drop significantly in the post-issue period. Affiliated dealers experience 0.3 additional client interactions per week (statistically significant) only in the event month, and 0.1 fewer thereafter. This result suggests that they become the dominant market-makers of existing bonds in the event month, but the effect quickly reverses following the same pattern we observe for market making profits (Table VII). This result is also consistent with our finding that transaction volume drops after a spike in the event week (Figure 1).

Finally, comparing the magnitudes of the coefficients in Columns 1 (0.3) and 5 (0.2), roughly two-thirds of the increase in interactions (and of the subsequent drop) comes from the Top 10% of clients. Thus affiliated dealers' client list does get better with the event, though the effect is only temporary in the event month.

To put these coefficients in context, the unconditional mean number of clients at the event level in each classification is 4.19, 0.54, 3.65, 3.03, and 2.15, respectively. Compared to these numbers, the estimated differences in client numbers during the post-issuance period appears to be economically insignificant, except that affiliated dealers interacted with about 7% more clients only in the event month. Overall, our results constitute a further rejection of the alternative explanation considered in this subsection: affiliated dealers do not gain permanent (or even persistent) access to a better client list than unaffiliated ones.

[Insert Table IX here]

Summarizing, in this section we have sought evidence that affiliated dealers may be engaging in aggressive bidding because they have some form of trading advantage—be it central position, information, or client access—and they can afford to bid more because they know they will be able to sell the bonds for more. Taken together, the evidence we uncovered does not support this theory. The evidence does show that affiliated dealers gain a dominant positions as market makers of the existing bonds: *only* in the event month, they experience a relative increase in trading volume (Figure 1), centrality (Table VIII), and more frequent interactions with high-volume clients (Table IX), resulting in an increase in market-making profits (Columns (2) and (5) of Table VII). All these effects, however, are reversed already in the following month.

The evidence also shows that affiliated dealers do take on existing bonds in their inventory (Columns (1) and (4) of Table VII). This inventory is significantly higher than that of unaffiliated dealers for at least two months after the event. However, this increase in inventory is not associated with excess profits (Columns (3) and (6) of Table VII). Given that most inventory is gone by month 5, and that we include unrealized gains on inventory in our measure of position-taking profits, it is unlikely that additional profits would appear outside of our event window. Moreover, this increase in inventory begins in the event month, i.e., pre-issue aggressive bidding is unlikely to be motivated by a desire to accumulate a position because it does not build any inventory.

VI. Conclusion

In this paper, we show that the underwriter's role in the bond market can be broader than commonly understood because a typical issuer already has outstanding bonds prior to the issue of a new bond. We show that, upon a new corporate bond issue, the underwriter and its affiliated broker-dealer arm support the new bond's price even prior to the issue date using the issuer's existing bonds. In particular, we compare contemporaneous transactions of the issuer's existing bonds carried out by affiliated and unaffiliated dealers. We find that affiliated dealers bid aggressively, that is, they pay a significantly higher price for the same bonds at the same time. Such an atypical trading pattern produces a higher reference price, visible to all potential investors in the new bond.

Our results suggest that this trading pattern is driven by the underwriter's incentive to lower the issuer's borrowing cost, i.e., to sell the new bond at a higher price. We rule out other plausible explanations for aggressive bidding, such as covering short positions established for hedging or other reasons, or building long positions that will result in subsequent trading profits. Instead, we find that upon the issuance of a new bond the affiliated dealers act as main brokers that facilitate the matching between the existing bonds (often underwritten by other entities) and new investors in the secondary market.

In a broader sense, our findings imply that the underwriter's client catering motive may induce a wealth transfer from primary market investors to the issuer. Our paper further contributes to the debate on the conflicts of interest stemming from the multiple roles played by financial institutions.

REFERENCES

- Aggarwal, Reena, 2000, Stabilization activities by underwriters after initial public offerings, *Journal of Finance* 55, 1075–1103.
- Baker, Malcolm, Xin Pan, and Jeffrey Wurgler, 2012, The effect of reference point prices on mergers and acquisitions, *Journal of Financial Economics* 106, 49–71.
- Bao, Jack, Maureen O’Hara, and Xing (Alex) Zhou, 2018, The Volcker Rule and Market-Making in Times of Stress, *Journal of Financial Economics* forthcoming.
- Bessembinder, Hendrik, Stacey E. Jacobsen, William F. Maxwell, and Kumar Venkataraman, 2018, Capital Commitment and Illiquidity in Corporate Bonds, *Journal of Finance* 73, 1615–1661.
- Biais, Bruno, and Richard C Green, 2007, The microstructure of the bond market in the 20th century, *Research Showcase @ CMU* 8, 134–183.
- Chen, Ting, and Xiumin Martin, 2011, Do Bank-Affiliated Analysts Benefit from Lending Relationships?, *Journal of Accounting Research* 49, 633–675.
- Chiang, Yao-Min, Michelle Lowry, and Yiming Qian, 2018, The information advantage of underwriters in IPOs, *Management Science* forthcoming.
- Choi, Jaewon, and Yesol Huh, 2016, Customer Liquidity Provision: Implications for Corporate Bond Transaction Costs, Federal Reserve Board Working Paper.
- Corwin, Shane, 2003, The determinants of underpricing for seasoned equity offers, *Journal of Finance* 58, 2249–2279.
- Drucker, Steven, and Manju Puri, 2005, So what do I get? The bank’s view of lending relationships, *Journal of Finance* LX, 2763–2799.
- Ellis, Katrina, Roni Michaely, and Maureen O’Hara, 2000, When the underwriter is the market maker: An examination of trading in the IPO aftermarket, *Journal of Finance* 55, 1039–1047.
- Gande, Amar, Manju Puri, Anthony Saunders, and Ingo Walter, 1997, Bank Underwriting of Debt Securities: Modern Evidence, *Review of Financial Studies* 10, 1175–1202.
- Goldstein, Michael A., and Edith S. Hotchkiss, 2007, Dealer behavior and the trading of newly issued corporate bonds, Working paper.
- Goldstein, Michael A., and Edith S. Hotchkiss, 2018, Providing Liquidity in an Illiquid Market: Dealer Behavior in U.S. Corporate Bonds, *Journal of Financial Economics* forthcoming.
- Goldstein, Michael A., Edith S. Hotchkiss, and Erik R. Sirri, 2007, Transparency and liquidity: A controlled experiment on corporate bonds, *Review of Financial Studies* 20, 235–273.
- Golez, Benjamin, and Jose M. Marin, 2015, Price support by bank-affiliated mutual funds, *Journal of Financial Economics* 115, 614–638.
- Green, Richard C., Burton Hollifield, and Norman Schürhoff, 2007, Dealer intermediation and price behavior in the aftermarket for new bond issues, *Journal of Financial Economics* 86, 643–682.
- Li, Dan, and Norman Schürhoff, 2018, Dealer Networks, *Journal of Finance* forthcoming.

- Ljungqvist, Alexander, Felicia Marston, and William J. Wilhelm, 2006, Competing for securities underwriting mandates: Banking relationships and analyst recommendations, *Journal of Finance* 61, 301–340.
- Lou, Dong, Hongjun Yan, and Jinfan Zhang, 2013, Anticipated and repeated shocks in liquid markets, *Review of Financial Studies* 26, 1890–1912.
- Mola, Simona, and Massimo Guidolin, 2009, Affiliated mutual funds and analyst optimism, *Journal of Financial Economics* 93, 108–137.
- Nagler, Florian, and Giorgio Ottonello, 2018, Structural changes in corporate bond underpricing, BAFFI CAREFIN Centre Research Paper No. 2017–48. Available at SSRN: <https://ssrn.com/abstract=2896758>.
- O’Hara, Maureen, Yihui Wang, and Xing Zhou, 2017, The Execution Quality of Corporate Bonds, *Journal of Financial Economics* forthcoming, Cornell University Working Paper.
- Puri, Manju, 1996, Commercial banks in investment banking: Conflict of interest or certification role?, *Journal of Financial Economics* 40, 373–401.
- Schultz, Paul, 2017, Inventory Management by Corporate Bond Dealers, University of Notre Dame Working Paper.

Figure 1. Trading Volume of Existing Bonds around the Issuance

This figure shows the average dealer's trading volume (in millions of dollars) for an issuer's existing bonds. Week 0 is the event week, i.e., the week in which the issuer's new bond is issued. Each panel represents a different combination of trade side (Buy/Sell) and counterparty (Dealer/Client). The unit of observation is a Dealer-Event-Week. In a given week, we first sum the volume of each dealer's trades, and then average across affiliated dealers (solid line) and unaffiliated dealers (dashed line).

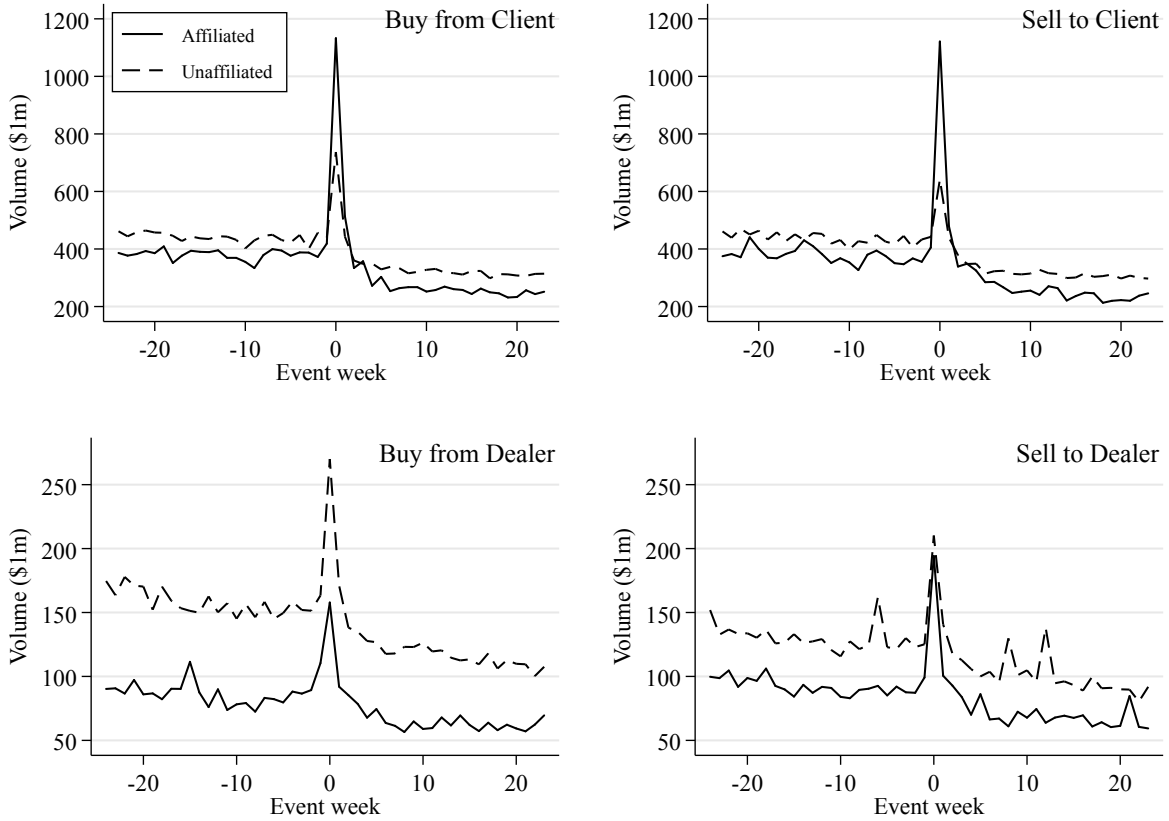


Figure 2. Price Regression at Monthly Resolution

This figure plots the point estimates of the interaction coefficients for “buy from dealer” trades under various specifications. For the baseline specification, estimated on the whole sample, the figure shows the difference-in-differences terms (β_m) in Equation (1). For the subsample specifications, the figure shows the sum of the triple-differences terms (γ_m) and baseline difference terms (β_m) in Equations (2) and (3). The unit of observation for each regression is a Dealer \times Bond \times Event \times Week. Each specification includes Dealer \times Bond \times Event fixed effects and Calendar Week fixed effects. Standard errors are clustered at the Dealer \times Bond \times Event level

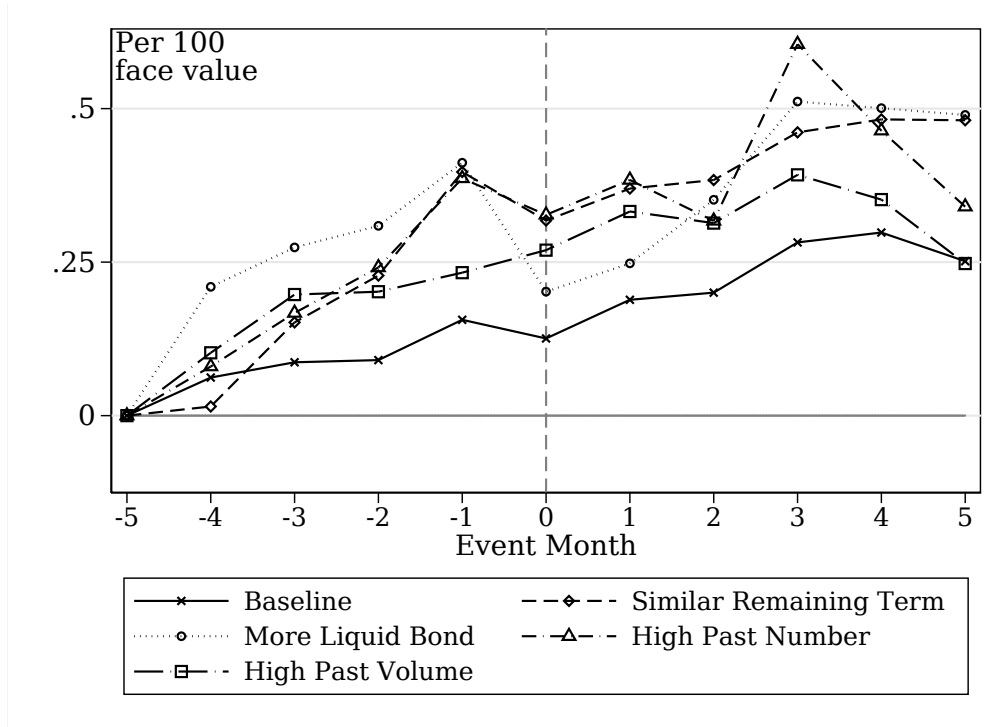


Figure 3. New-Issue Trading: Time Trend of Market Share

This figure plots the market share of new-issue trading for underwriter-affiliated (solid line) and unaffiliated dealers (dashed line). Market share is measured as percent of total weekly trading volume with regard to the newly issued security alone. Week 0 indicates the issue event week. The unit of observation is a Dealer \times Event \times Bond \times Week.

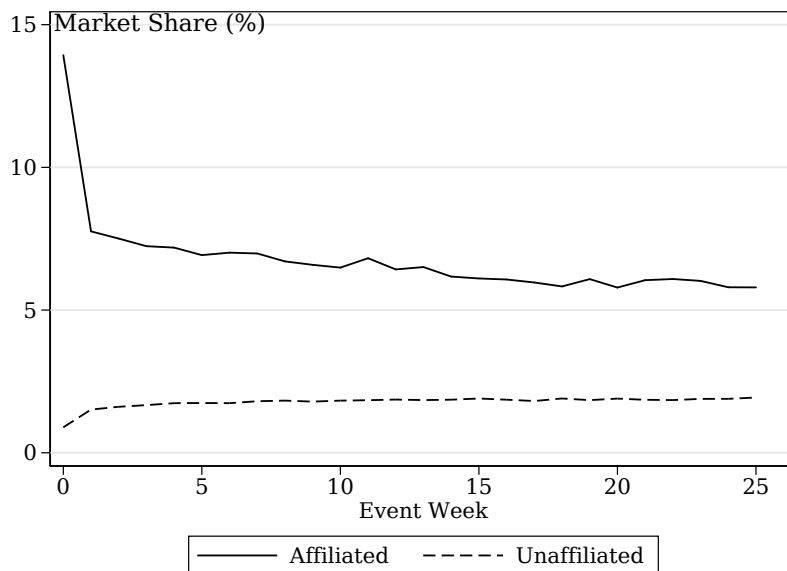


Table I. Summary Statistics

Total No. Dealers indicates the total number of dealers in a given year. The “Total” row does not equal the sum of the individual rows because most dealers appear in most years. *Total Volume* (in billions of U.S. Dollars) is simply the sum of the value of all transactions in our version of the TRACE database. *No. Included Dealers* indicates the number of dealers that we consider to be potential underwriters because they are associated with at least one event in the current, previous, or next year. All dealers under the same ultimate parent count as just one dealer. *% Total Volume by Included Dealers* indicates the fraction of total TRACE volume attributable to the dealers we have included. The percentage is large, indicating that underwriter-affiliated dealers are very large compared to the average TRACE dealer. *% Total Volume in Final Sample* indicates the fraction of total TRACE volume that we use in our final sample. This number is much smaller because, among other reasons, most of the trading done by underwriter-dealers is not around an issue event. *% Final Sample Volume from Principal Trades* indicates the fraction of our final sample consisting of trades made by the dealer as a principal (as opposed to agent). *No. Affiliated Dealers* is the number of dealers we identify as affiliated. *% Final Sample by Affiliated Dealers* indicates the fraction of volume in the final sample that is attributable to affiliated dealers.

Year	Total No. Dealers	Total Volume (\$B)	No. Included Dealers	% Total Volume by Included Dealers	% Total Volume in Final Sample	% Final Sample Volume from Principal Trades	No. Aff. Dealers	% Final Sample by Aff. Dealers
2005	1,587	5,830	74	75.5%	5.9%	97.9%	26	30.2%
2006	1,427	7,539	79	75.4%	8.9%	97.8%	26	33.5%
2007	1,349	6,820	75	77.5%	11.1%	98.0%	30	34.2%
2008	1,381	5,796	66	79.9%	9.2%	97.7%	27	31.9%
2009	1,448	7,752	69	76.8%	11.4%	97.8%	26	31.0%
2010	1,435	9,040	71	77.5%	13.4%	98.4%	28	39.6%
2011	1,392	8,575	75	77.5%	13.2%	98.3%	36	41.8%
2012	1,295	9,955	76	79.8%	16.9%	97.8%	39	51.2%
2013	1,212	9,481	74	83.3%	17.6%	97.2%	37	50.2%
2014	1,124	10,694	70	85.4%	16.8%	97.7%	39	47.5%
2015	1,042	7,958	66	84.1%	20.0%	97.4%	36	50.1%
Total	2,674	89,440	107	79.7%	13.7%	97.8%	52	43.5%

Table II. Price Regression

This table shows coefficient estimates from Equation (1). The sample consists of all transactions of an issuer's existing bonds in a window centered on the issuance of a new bond. In each column, the dependent variable is the transaction price for a different trade type. Transactions differ with respect to two aspects: whether a dealer buys or sells a bond (Buy or Sell) and whether the dealer's counterparty is another dealer or a client (Dealer or Client). The baseline coefficients (Month = m) measure the level of the dependent variable in month m relative to month -5 for dealers unaffiliated with the issue underwriter. The interaction coefficients (Month = $m \times$ Affiliate = 1) measure the difference in month m between affiliated and unaffiliated dealers. The unit of observation for each regression is a Dealer \times Bond \times Event \times Week. Each specification includes Dealer \times Bond \times Event fixed effects and calendar Week fixed effects. Standard errors are clustered at the Dealer \times Bond \times Event level. t -statistics are reported in parentheses. The number of stars (*) represents statistical significance at 10% (*), 5% (**), and 1% (***)

	Dependent Variable: Weekly Average Price			
	(1) Buy from Dealer	(2) Buy from Client	(3) Sell to Dealer	(4) Sell to Client
Month=-4	0.10*** (4.32)	0.03 (1.45)	0.05** (2.18)	0.04** (2.39)
Month=-3	0.05* (1.89)	-0.04* (-1.75)	-0.02 (-0.71)	0.02 (0.84)
Month=-2	0.01 (0.19)	-0.05* (-1.67)	-0.06* (-1.65)	-0.06* (-1.88)
Month=-1	0.06 (1.26)	0.07* (1.76)	0.04 (0.99)	0.05 (1.29)
Month=0	0.08 (1.42)	0.07 (1.63)	0.00 (0.08)	0.06 (1.31)
Month=1	0.23*** (3.77)	0.22*** (4.05)	0.17*** (2.98)	0.25*** (4.71)
Month=2	0.25*** (3.56)	0.27*** (4.39)	0.17** (2.57)	0.26*** (4.27)
Month=3	0.10 (1.24)	0.17** (2.51)	0.03 (0.39)	0.15** (2.15)
Month=4	0.15* (1.75)	0.21*** (2.77)	0.08 (0.93)	0.21*** (2.85)
Month=5	0.16* (1.66)	0.22*** (2.62)	0.09 (0.96)	0.17** (2.07)
Month=-4 \times Affiliate=1	0.06 (1.20)	-0.00 (-0.08)	-0.08* (-1.85)	0.00 (0.01)
Month=-3 \times Affiliate=1	0.09 (1.42)	0.03 (0.70)	-0.04 (-0.79)	0.02 (0.41)
Month=-2 \times Affiliate=1	0.09 (1.35)	0.01 (0.11)	-0.03 (-0.60)	0.01 (0.15)
Month=-1 \times Affiliate=1	0.16** (2.21)	0.02 (0.45)	-0.08 (-1.33)	0.05 (0.87)
Month=0 \times Affiliate=1	0.13* (1.66)	0.04 (0.65)	-0.07 (-1.12)	0.02 (0.26)
Month=1 \times Affiliate=1	0.19** (2.41)	0.06 (1.02)	-0.01 (-0.22)	0.08 (1.31)
Month=2 \times Affiliate=1	0.20** (2.44)	0.07 (1.18)	-0.01 (-0.13)	0.09 (1.48)
Month=3 \times Affiliate=1	0.28*** (3.29)	0.11* (1.74)	0.13* (1.81)	0.17*** (2.60)
Month=4 \times Affiliate=1	0.30*** (3.32)	0.17** (2.56)	0.09 (1.19)	0.21*** (3.12)
Month=5 \times Affiliate=1	0.25*** (2.65)	0.10 (1.39)	0.03 (0.37)	0.23*** (3.15)
Dealer \times Event \times Bond F.E.	Y	Y	Y	Y
Week F.E.	Y	Y	Y	Y
N. Obs.	671,217	890,190	673,576	899,440
Adj. R^2	0.94	0.93	0.94	0.93

Table III. Price Regression with Similar Maturity

This table shows coefficient estimates from Equation (2). The sample consists of all transactions of an issuer's existing bonds in a window centered on the issuance of a new bond. The regression specification contains interaction terms for a special subsample of similar-maturity bonds, defined as bonds whose remaining maturity is within ± 2 years of the new bond's maturity. The baseline coefficients (Month = m) are omitted. The interaction coefficients (Month = $m \times$ Affiliate = 1) measure the difference in month m between affiliated and unaffiliated dealers for transactions not belonging to the special subsample. The triple interaction coefficients (Month = $m \times$ Affiliate = 1 \times Similar Remaining Term (± 2 yr) = 1) measure the additional effect in month m for transactions belonging to the special subsample. The unit of observation for each regression is a Dealer \times Bond \times Event \times Week. Each specification includes Dealer \times Bond \times Event fixed effects and calendar Week fixed effects. Standard errors are clustered at the Dealer \times Bond \times Event level. t -statistics are reported in parentheses. The number of stars (*) represents statistical significance at 10% (*), 5% (**), and 1% (***)).

	Dependent Variable: Weekly Average Price			
	(1) Buy from Dealer	(2) Buy from Client	(3) Sell to Dealer	(4) Sell to Client
Month=-4 \times Affiliate=1	0.03 (0.46)	0.04 (0.58)	-0.02 (-0.33)	-0.02 (-0.38)
Month=-3 \times Affiliate=1	0.05 (0.60)	0.05 (0.71)	0.02 (0.22)	0.01 (0.20)
Month=-2 \times Affiliate=1	0.04 (0.37)	-0.03 (-0.38)	-0.01 (-0.09)	-0.03 (-0.34)
Month=-1 \times Affiliate=1	0.07 (0.67)	0.05 (0.56)	-0.06 (-0.59)	0.06 (0.70)
Month=0 \times Affiliate=1	0.03 (0.26)	0.07 (0.75)	-0.04 (-0.40)	0.02 (0.20)
Month=1 \times Affiliate=1	0.02 (0.15)	0.07 (0.75)	-0.01 (-0.10)	0.08 (0.80)
Month=2 \times Affiliate=1	0.08 (0.66)	0.14 (1.46)	0.05 (0.45)	0.12 (1.15)
Month=3 \times Affiliate=1	0.22* (1.75)	0.21** (2.06)	0.15 (1.33)	0.22** (2.12)
Month=4 \times Affiliate=1	0.22* (1.65)	0.35*** (3.36)	0.21* (1.77)	0.27** (2.51)
Month=5 \times Affiliate=1	0.16 (1.16)	0.22** (2.01)	0.14 (1.13)	0.27** (2.37)
Month=-4 \times Affiliate=1 \times Similar Remaining Term (± 2 yr)=1	-0.02 (-0.16)	-0.03 (-0.32)	-0.10 (-1.04)	0.09 (1.03)
Month=-3 \times Affiliate=1 \times Similar Remaining Term (± 2 yr)=1	0.10 (0.72)	0.02 (0.16)	-0.01 (-0.05)	0.05 (0.45)
Month=-2 \times Affiliate=1 \times Similar Remaining Term (± 2 yr)=1	0.19 (1.22)	0.19 (1.62)	0.08 (0.57)	0.14 (1.16)
Month=-1 \times Affiliate=1 \times Similar Remaining Term (± 2 yr)=1	0.33** (2.02)	0.14 (1.17)	0.10 (0.74)	0.10 (0.78)
Month=0 \times Affiliate=1 \times Similar Remaining Term (± 2 yr)=1	0.29 (1.64)	0.10 (0.81)	0.13 (0.86)	0.13 (0.98)
Month=1 \times Affiliate=1 \times Similar Remaining Term (± 2 yr)=1	0.35* (1.96)	0.15 (1.13)	0.09 (0.63)	0.09 (0.62)
Month=2 \times Affiliate=1 \times Similar Remaining Term (± 2 yr)=1	0.31* (1.67)	0.02 (0.17)	-0.03 (-0.20)	0.01 (0.07)
Month=3 \times Affiliate=1 \times Similar Remaining Term (± 2 yr)=1	0.24 (1.25)	-0.02 (-0.14)	0.06 (0.39)	0.06 (0.36)
Month=4 \times Affiliate=1 \times Similar Remaining Term (± 2 yr)=1	0.27 (1.33)	-0.11 (-0.71)	-0.12 (-0.70)	0.09 (0.55)
Month=5 \times Affiliate=1 \times Similar Remaining Term (± 2 yr)=1	0.32 (1.55)	-0.01 (-0.08)	-0.07 (-0.39)	0.05 (0.31)
Dealer \times Event \times Bond F.E.	Y	Y	Y	Y
Week F.E.	Y	Y	Y	Y
N. Obs.	503,283	627,200	500,994	627,106
Adj. R^2	0.95	0.94	0.94	0.93

Table IV. Price Regression with Relatively Higher Liquidity

This table shows coefficient estimates from Equation (2). The sample consists of all transactions of an issuer's existing bonds in a window centered on the issuance of a new bond. The regression specification contains interaction terms for a special subsample of more liquid bonds. A bond is classified as more liquid when its past transaction volume for the past 3 months prior to the issuance time is in the top quartile of all existing bonds of the same issuer of each issuance event. The baseline coefficients (Month = m) are omitted. The interaction coefficients (Month = $m \times$ Affiliate = 1) measure the difference in month m between affiliated and unaffiliated dealers for transactions not belonging to the special subsample. The triple interaction coefficients (Month = $m \times$ Affiliate = 1 \times More Liquid Bond (top 25%) = 1) measure the additional effect in month m for transactions belonging to the special subsample. The unit of observation for each regression is a Dealer \times Bond \times Event \times Week. Each specification includes Dealer \times Bond \times Event fixed effects and calendar Week fixed effects. Standard errors are clustered at the Dealer \times Bond \times Event level. t -statistics are reported in parentheses. The number of stars (*) represents statistical significance at 10% (*), 5% (**), and 1% (***)

	Dependent Variable: Weekly Average Price			
	(1) Buy from Dealer	(2) Buy from Client	(3) Sell to Dealer	(4) Sell to Client
Month=-4 \times Affiliate=1	0.01 (0.25)	0.02 (0.38)	-0.05 (-1.06)	-0.01 (-0.24)
Month=-3 \times Affiliate=1	0.03 (0.46)	0.06 (1.10)	0.00 (0.00)	0.07 (1.32)
Month=-2 \times Affiliate=1	0.02 (0.24)	0.04 (0.67)	-0.01 (-0.09)	0.02 (0.26)
Month=-1 \times Affiliate=1	0.05 (0.60)	0.06 (1.05)	-0.06 (-0.86)	0.06 (0.99)
Month=0 \times Affiliate=1	0.08 (0.92)	0.07 (1.18)	-0.05 (-0.70)	0.06 (0.92)
Month=1 \times Affiliate=1	0.13 (1.49)	0.09 (1.32)	-0.02 (-0.27)	0.12 (1.61)
Month=2 \times Affiliate=1	0.13 (1.39)	0.15** (2.07)	0.02 (0.27)	0.15** (1.99)
Month=3 \times Affiliate=1	0.17* (1.82)	0.20*** (2.73)	0.14* (1.66)	0.21*** (2.69)
Month=4 \times Affiliate=1	0.21** (2.09)	0.28*** (3.70)	0.13 (1.49)	0.28*** (3.45)
Month=5 \times Affiliate=1	0.15 (1.41)	0.18** (2.18)	0.06 (0.61)	0.25*** (2.91)
Month=-4 \times Affiliate=1 \times More Liquid Bond (top 25%)=1	0.20 (1.55)	-0.02 (-0.20)	-0.04 (-0.37)	0.04 (0.48)
Month=-3 \times Affiliate=1 \times More Liquid Bond (top 25%)=1	0.24 (1.56)	-0.05 (-0.50)	-0.06 (-0.50)	-0.13 (-1.21)
Month=-2 \times Affiliate=1 \times More Liquid Bond (top 25%)=1	0.29* (1.72)	-0.05 (-0.42)	-0.04 (-0.33)	0.01 (0.05)
Month=-1 \times Affiliate=1 \times More Liquid Bond (top 25%)=1	0.37** (2.09)	-0.08 (-0.65)	-0.03 (-0.20)	-0.04 (-0.33)
Month=0 \times Affiliate=1 \times More Liquid Bond (top 25%)=1	0.12 (0.66)	-0.11 (-0.89)	-0.06 (-0.42)	-0.13 (-1.04)
Month=1 \times Affiliate=1 \times More Liquid Bond (top 25%)=1	0.12 (0.62)	-0.10 (-0.80)	0.01 (0.07)	-0.14 (-1.08)
Month=2 \times Affiliate=1 \times More Liquid Bond (top 25%)=1	0.22 (1.13)	-0.22 (-1.61)	-0.08 (-0.52)	-0.18 (-1.29)
Month=3 \times Affiliate=1 \times More Liquid Bond (top 25%)=1	0.34 (1.63)	-0.28* (-1.84)	-0.02 (-0.11)	-0.14 (-0.95)
Month=4 \times Affiliate=1 \times More Liquid Bond (top 25%)=1	0.29 (1.33)	-0.30* (-1.96)	-0.11 (-0.60)	-0.17 (-1.13)
Month=5 \times Affiliate=1 \times More Liquid Bond (top 25%)=1	0.34 (1.44)	-0.22 (-1.39)	-0.10 (-0.53)	-0.09 (-0.55)
Dealer \times Event \times Bond F.E.	Y	Y	Y	Y
Week F.E.	Y	Y	Y	Y
N. Obs.	651,343	847,267	653,037	856,307
Adj. R^2	0.94	0.93	0.94	0.93

Table V. Price Regression with Past Issue Frequency

This table shows coefficient estimates from Equation (3). The sample consists of all transactions of an issuer's existing bonds in a window centered on the issuance of a new bond. The regression specification contains interaction terms for a special subsample of events by high-frequency issuers. High-frequency issuers belong to the top quartile of issuers by past issue frequency, measured as that issuer's total number of issues over the past three years. Issuers are ranked within each calendar month. The baseline coefficients (Month = m) are omitted. The interaction coefficients (Month = $m \times$ Affiliate = 1) measure the difference in month m between affiliated and unaffiliated dealers for transactions not belonging to the special subsample. The triple interaction coefficients (Month = $m \times$ Affiliate = 1 \times High Past Number (top 25%) = 1) measure the additional effect in month m for transactions belonging to the special subsample. The unit of observation for each regression is a Dealer \times Bond \times Event \times Week. Each specification includes Dealer \times Bond \times Event fixed effects and calendar Week fixed effects. Standard errors are clustered at the Dealer \times Bond \times Event level. t -statistics are reported in parentheses. The number of stars (*) represents statistical significance at 10% (*), 5% (**), and 1% (***)

	Dependent Variable: Weekly Average Price			
	(1) Buy from Dealer	(2) Buy from Client	(3) Sell to Dealer	(4) Sell to Client
Month=-4 \times Affiliate=1	0.05 (0.75)	-0.03 (-0.54)	-0.10* (-1.73)	0.01 (0.31)
Month=-3 \times Affiliate=1	0.03 (0.38)	0.01 (0.24)	-0.13* (-1.73)	0.02 (0.26)
Month=-2 \times Affiliate=1	-0.01 (-0.09)	-0.03 (-0.43)	-0.13 (-1.63)	-0.00 (-0.07)
Month=-1 \times Affiliate=1	0.01 (0.11)	-0.05 (-0.71)	-0.19** (-2.34)	0.01 (0.12)
Month=0 \times Affiliate=1	-0.01 (-0.07)	-0.03 (-0.43)	-0.23*** (-2.75)	0.01 (0.10)
Month=1 \times Affiliate=1	0.06 (0.59)	-0.02 (-0.31)	-0.18** (-2.07)	0.05 (0.65)
Month=2 \times Affiliate=1	0.13 (1.24)	-0.02 (-0.20)	-0.14 (-1.50)	0.09 (1.10)
Month=3 \times Affiliate=1	0.06 (0.57)	-0.03 (-0.41)	-0.01 (-0.12)	0.05 (0.62)
Month=4 \times Affiliate=1	0.19 (1.56)	-0.00 (-0.03)	-0.09 (-0.80)	0.13 (1.38)
Month=5 \times Affiliate=1	0.20 (1.54)	-0.03 (-0.29)	-0.12 (-1.09)	0.21** (2.05)
Month=-4 \times Affiliate=1 \times High Past Number (top 25%)=1	0.03 (0.28)	0.05 (0.71)	0.06 (0.69)	-0.04 (-0.51)
Month=-3 \times Affiliate=1 \times High Past Number (top 25%)=1	0.14 (1.12)	0.05 (0.49)	0.21** (1.98)	0.01 (0.08)
Month=-2 \times Affiliate=1 \times High Past Number (top 25%)=1	0.25* (1.88)	0.09 (0.85)	0.23** (1.97)	0.03 (0.30)
Month=-1 \times Affiliate=1 \times High Past Number (top 25%)=1	0.38*** (2.68)	0.19* (1.74)	0.27** (2.24)	0.10 (0.89)
Month=0 \times Affiliate=1 \times High Past Number (top 25%)=1	0.33** (2.18)	0.17 (1.52)	0.40*** (3.07)	0.02 (0.17)
Month=1 \times Affiliate=1 \times High Past Number (top 25%)=1	0.32** (2.05)	0.20* (1.73)	0.41*** (3.02)	0.07 (0.54)
Month=2 \times Affiliate=1 \times High Past Number (top 25%)=1	0.19 (1.12)	0.22* (1.75)	0.32** (2.24)	0.01 (0.11)
Month=3 \times Affiliate=1 \times High Past Number (top 25%)=1	0.54*** (3.12)	0.36*** (2.66)	0.35** (2.37)	0.28** (2.06)
Month=4 \times Affiliate=1 \times High Past Number (top 25%)=1	0.28 (1.54)	0.41*** (3.04)	0.43*** (2.73)	0.20 (1.46)
Month=5 \times Affiliate=1 \times High Past Number (top 25%)=1	0.14 (0.75)	0.31** (2.13)	0.38** (2.26)	0.06 (0.42)
Dealer \times Event \times Bond F.E.	Y	Y	Y	Y
Week F.E.	Y	Y	Y	Y
N. Obs.	671,217	890,190	673,576	899,440
Adj. R^2	0.94	0.93	0.94	0.93

Table VI. Price Regression with Past Issue Volume

This table shows coefficient estimates from Equation (3). The sample consists of all transactions of an issuer's existing bonds in a window centered on the issuance of a new bond. The regression specification contains interaction terms for a special subsample of events by high-volume issuers. High-volume issuers belong to the top quartile of issuers by past issue volume, measured as that issuer's total dollar value of issues over the past three years. Issuers are ranked within each calendar month. The baseline coefficients (Month = m) are omitted. The interaction coefficients (Month = $m \times$ Affiliate = 1) measure the difference in month m between affiliated and unaffiliated dealers for transactions not belonging to the special subsample. The triple interaction coefficients (Month = $m \times$ Affiliate = 1 \times High Past Number (top 25%) = 1) measure the additional effect in month m for transactions belonging to the special subsample. The unit of observation for each regression is a Dealer \times Bond \times Event \times Week. Each specification includes Dealer \times Bond \times Event fixed effects and calendar Week fixed effects. Standard errors are clustered at the Dealer \times Bond \times Event level. t -statistics are reported in parentheses. The number of stars (*) represents statistical significance at 10% (*), 5% (**), and 1% (***)

	Dependent Variable: Weekly Average Price			
	(1) Buy from Dealer	(2) Buy from Client	(3) Sell to Dealer	(4) Sell to Client
Month=-4 \times Affiliate=1	-0.01 (-0.08)	-0.11* (-1.83)	-0.26*** (-3.31)	-0.07 (-1.13)
Month=-3 \times Affiliate=1	-0.11 (-1.09)	-0.09 (-1.28)	-0.35*** (-3.67)	-0.01 (-0.13)
Month=-2 \times Affiliate=1	-0.09 (-0.80)	-0.15* (-1.89)	-0.37*** (-3.64)	-0.10 (-1.16)
Month=-1 \times Affiliate=1	0.04 (0.34)	-0.19** (-2.15)	-0.43*** (-3.72)	-0.03 (-0.33)
Month=0 \times Affiliate=1	-0.12 (-0.92)	-0.18** (-2.03)	-0.48*** (-4.06)	-0.11 (-1.15)
Month=1 \times Affiliate=1	-0.07 (-0.49)	-0.20** (-2.10)	-0.44*** (-3.43)	-0.08 (-0.77)
Month=2 \times Affiliate=1	0.01 (0.09)	-0.17* (-1.68)	-0.41*** (-3.00)	0.01 (0.08)
Month=3 \times Affiliate=1	0.09 (0.60)	-0.15 (-1.39)	-0.20 (-1.36)	0.05 (0.48)
Month=4 \times Affiliate=1	0.22 (1.28)	-0.10 (-0.83)	-0.25 (-1.57)	0.04 (0.35)
Month=5 \times Affiliate=1	0.28 (1.55)	-0.06 (-0.42)	-0.23 (-1.36)	0.20 (1.42)
Month=-4 \times Affiliate=1 \times High Past Volume (top 25%)=1	0.11 (1.01)	0.16** (2.10)	0.27*** (2.82)	0.11 (1.37)
Month=-3 \times Affiliate=1 \times High Past Volume (top 25%)=1	0.31** (2.42)	0.18* (1.95)	0.45*** (3.95)	0.04 (0.42)
Month=-2 \times Affiliate=1 \times High Past Volume (top 25%)=1	0.29** (2.09)	0.23** (2.28)	0.50*** (4.03)	0.16 (1.47)
Month=-1 \times Affiliate=1 \times High Past Volume (top 25%)=1	0.19 (1.27)	0.32*** (2.92)	0.51*** (3.78)	0.11 (0.97)
Month=0 \times Affiliate=1 \times High Past Volume (top 25%)=1	0.39** (2.44)	0.32*** (2.82)	0.61*** (4.28)	0.18 (1.50)
Month=1 \times Affiliate=1 \times High Past Volume (top 25%)=1	0.40** (2.39)	0.38*** (3.20)	0.62*** (4.14)	0.23* (1.81)
Month=2 \times Affiliate=1 \times High Past Volume (top 25%)=1	0.30* (1.71)	0.36*** (2.83)	0.58*** (3.68)	0.12 (0.95)
Month=3 \times Affiliate=1 \times High Past Volume (top 25%)=1	0.30 (1.61)	0.39*** (2.88)	0.48*** (2.88)	0.17 (1.21)
Month=4 \times Affiliate=1 \times High Past Volume (top 25%)=1	0.13 (0.65)	0.39*** (2.76)	0.50*** (2.76)	0.25* (1.67)
Month=5 \times Affiliate=1 \times High Past Volume (top 25%)=1	-0.04 (-0.17)	0.23 (1.45)	0.38** (1.97)	0.05 (0.29)
Dealer \times Event \times Bond F.E.	Y	Y	Y	Y
Week F.E.	Y	Y	Y	Y
N. Obs.	671,217	890,190	673,576	899,440
Adj. R^2	0.94	0.93	0.94	0.93

Table VII. Alternative Hypotheses

This table shows coefficient estimates from Equations (4), (6) and (7) to test three alternative hypotheses described in Section V. For each hypothesis, we use dependent variables in basis points and dollars, namely: inventory relative to new issue size (Column 1), market-making (MM) return (2), position-taking (PT) return (3), dollar inventory (4), dollar MM profit (5) and dollar PT profit (6). The dependent variable is in basis points in Columns (1)–(3) and thousand dollars in Columns (4)–(6). The baseline coefficients (Month = m) measure the level of the dependent variable in month m relative to month -5 for dealers unaffiliated with the issue underwriter. The interaction coefficients (Month = $m \times$ Affiliate = 1) measure the difference in month m between affiliated and unaffiliated dealers. One observation is a Dealer \times Week \times Event in Columns (1) and (4)–(6), and a Dealer \times Week \times Event \times Bond in Columns (2)–(3). The respective specifications include Dealer \times Event fixed effects and Dealer \times Event \times Bond fixed effects. All specifications include calendar Week fixed effects. Standard errors are clustered at the Dealer \times Event level for Columns (1) and (4)–(6), and at the Dealer \times Event \times Bond level for Columns (2)–(3). t -statistics are reported in parentheses. The number of stars (*) represents statistical significance at 10% (*), 5% (**), and 1% (***)

	Basis Points			Dollar		
	(1) Relative Inventory	(2) Market- Making Return	(3) Position- Taking Return	(4) Inventory Value	(5) Market- Making Profit	(6) Position- Taking Profit
Month=-4	-0.4 (-1.22)	-1.0 (-1.28)	0.6 (0.51)	-8.1 (-0.34)	0.0*** (3.73)	-0.0 (-0.01)
Month=-3	-0.8 (-1.58)	-2.9*** (-2.74)	0.3 (0.19)	10.4 (0.26)	0.1*** (5.50)	4.7 (0.78)
Month=-2	-0.1 (-0.11)	-2.6* (-1.76)	2.5 (1.03)	61.7 (1.28)	0.1*** (6.09)	5.3 (0.63)
Month=-1	0.6 (0.87)	-3.3* (-1.89)	4.4 (1.46)	95.2* (1.73)	0.2*** (6.66)	8.5 (0.79)
Month=0	2.8*** (3.46)	-4.3** (-2.01)	6.9* (1.85)	292.2*** (4.68)	0.2*** (6.73)	16.8 (1.26)
Month=1	3.3*** (3.71)	-5.5** (-2.19)	4.5 (1.02)	296.6*** (4.34)	0.2*** (4.72)	8.2 (0.52)
Month=2	2.6*** (2.76)	-7.0** (-2.37)	5.9 (1.15)	245.2*** (3.39)	0.2*** (4.81)	11.5 (0.63)
Month=3	2.2** (2.25)	-7.1** (-2.16)	6.1 (1.04)	233.6*** (3.15)	0.2*** (4.85)	10.5 (0.51)
Month=4	2.3** (2.15)	-7.5** (-2.02)	6.5 (0.99)	191.3*** (2.61)	0.3*** (5.02)	13.9 (0.60)
Month=5	2.5** (2.27)	-8.9** (-2.17)	9.0 (1.24)	182.6** (2.36)	0.3*** (4.98)	22.3 (0.86)
Month=-4 \times Affiliate=1	-0.4 (-0.19)	-2.3 (-1.60)	-0.4 (-0.11)	-101.4 (-0.76)	-0.0 (-0.26)	6.9 (0.35)
Month=-3 \times Affiliate=1	-1.3 (-0.46)	-0.2 (-0.13)	3.4 (0.96)	-31.5 (-0.16)	-0.0 (-0.91)	16.8 (0.85)
Month=-2 \times Affiliate=1	0.0 (0.01)	-0.2 (-0.11)	2.4 (0.69)	180.3 (0.60)	-0.1 (-1.56)	3.4 (0.18)
Month=-1 \times Affiliate=1	0.1 (0.03)	-2.5 (-1.57)	-2.4 (-0.69)	110.5 (0.30)	-0.1 (-1.26)	-0.3 (-0.02)
Month=0 \times Affiliate=1	16.9*** (3.47)	-4.3*** (-2.79)	10.5*** (2.86)	966.7* (1.80)	0.3*** (5.86)	29.3 (1.48)
Month=1 \times Affiliate=1	13.0** (2.53)	-2.0 (-1.18)	2.5 (0.72)	745.3 (1.32)	-0.2*** (-4.94)	30.2 (1.57)
Month=2 \times Affiliate=1	7.6 (1.41)	-2.1 (-1.32)	1.9 (0.55)	369.7 (0.64)	-0.2*** (-4.84)	-15.7 (-0.84)
Month=3 \times Affiliate=1	6.2 (1.12)	-0.8 (-0.49)	-0.4 (-0.12)	356.7 (0.60)	-0.3*** (-5.11)	10.5 (0.54)
Month=4 \times Affiliate=1	7.7 (1.37)	-2.1 (-1.19)	5.5 (1.57)	399.4 (0.65)	-0.2*** (-4.05)	19.4 (1.02)
Month=5 \times Affiliate=1	11.1* (1.93)	-3.2* (-1.78)	1.0 (0.28)	413.0 (0.67)	-0.3*** (-5.70)	-7.8 (-0.42)
Dealer \times Event F.E.	Y	N	N	Y	Y	Y
Dealer \times Event \times Bond F.E.	N	Y	Y	N	N	N
Week F.E.	Y	Y	Y	Y	Y	Y
N. Obs.	4,387,085	1,596,194	11,336,973	4,387,085	4,465,946	4,410,778
Adj. R^2	0.972	0.383	0.002	0.991	0.123	0.005

Table VIII. Dealer Centrality

This table shows coefficient estimates from Equation (5). The sample consists of all observations of a dealer transacting an issuer's existing bonds in a window centered on the issuance of a new bond. The dependent variable is a measure of dealer centrality. *Degree* measures the local connectivity of a dealer; *Closeness* measures the influence of a dealer respect to centrality; *Betweenness (Between)* measures the absolute position of a dealer in the dealer network; and *Eigen-Centrality* measures the overall importance of a dealer in the network. For a more detailed description, see Li and Schürhoff (2018). The baseline coefficients (Month = m) measure the level of the dependent variable in month m relative to month -5 for dealers unaffiliated with the issue underwriter. The interaction coefficients (Month = $m \times$ Affiliate = 1) measure the difference in month m between affiliated and unaffiliated dealers. The unit of observation for each regression is a Dealer \times Event \times Month. Each specification includes Dealer \times Event fixed effects and calendar Month fixed effects. Standard errors are clustered at the Dealer \times Event level. t -statistics are reported in parentheses. The number of stars (*) represents statistical significance at 10% (*), 5% (**), and 1% (***) .

	Network Centrality			
	(1) Degree	(2) Closeness	(3) Between	(4) Eigen-Centrality
Month=-4	0.001 (0.74)	0.003*** (2.76)	0.001 (0.45)	0.001 (0.85)
Month=-3	0.002 (1.42)	0.007*** (4.58)	0.002 (1.36)	0.003*** (2.86)
Month=-2	0.002 (1.34)	0.011*** (4.92)	0.002 (0.92)	0.004*** (3.03)
Month=-1	0.004* (1.82)	0.013*** (4.67)	0.002 (0.70)	0.005*** (2.87)
Month=0	0.004 (1.56)	0.019*** (5.80)	0.004 (1.00)	0.007*** (3.13)
Month=1	0.003 (0.84)	0.020*** (5.14)	0.004 (0.99)	0.008*** (3.04)
Month=2	0.002 (0.56)	0.020*** (4.32)	0.002 (0.47)	0.007** (2.37)
Month=3	0.004 (1.01)	0.027*** (5.26)	0.005 (0.94)	0.010*** (3.14)
Month=4	0.004 (0.92)	0.026*** (4.42)	0.006 (0.90)	0.010*** (2.68)
Month=5	0.005 (1.01)	0.031*** (4.77)	0.006 (0.80)	0.012*** (2.84)
Month=-4 \times Affiliate=1	0.002 (0.97)	0.004 (1.22)	0.007* (1.80)	0.004* (1.71)
Month=-3 \times Affiliate=1	0.004* (1.66)	0.002 (0.70)	0.002 (0.60)	0.002 (1.07)
Month=-2 \times Affiliate=1	0.002 (0.83)	0.001 (0.15)	0.001 (0.14)	0.001 (0.49)
Month=-1 \times Affiliate=1	0.002 (0.73)	0.003 (1.03)	0.003 (0.93)	0.002 (1.04)
Month=0 \times Affiliate=1	0.006** (2.35)	0.009** (2.54)	0.010*** (2.66)	0.006*** (2.82)
Month=1 \times Affiliate=1	-0.001 (-0.25)	0.001 (0.43)	0.001 (0.15)	0.003 (1.14)
Month=2 \times Affiliate=1	0.001 (0.29)	0.001 (0.19)	0.002 (0.63)	0.001 (0.56)
Month=3 \times Affiliate=1	-0.006** (-2.26)	-0.004 (-1.09)	-0.004 (-1.06)	-0.002 (-0.84)
Month=4 \times Affiliate=1	-0.005** (-2.03)	-0.004 (-1.08)	-0.005 (-1.41)	-0.003 (-1.39)
Month=5 \times Affiliate=1	-0.004 (-1.44)	-0.002 (-0.48)	-0.002 (-0.59)	-0.001 (-0.57)
Dealer \times Event F.E.	Y	Y	Y	Y
Month F.E.	Y	Y	Y	Y
N. Obs.	627,847	627,847	627,847	627,847
Adj. R^2	0.33	0.22	0.34	0.18

Table IX. Access to Clients

This table shows coefficient estimates from Equation (8). The sample consists of all observations of a dealer interacting with an insurance company in a window centered on the issuance of a new bond. The dependent variable is the number of transactions reported in NAIC Schedule D (Parts 3–5) matched with an underwriter-dealer. Column (1) uses all insurance companies matched with NAIC transaction data. Columns (2)–(5) use insurance companies that are classified as Bottom 50% or Top 50%, 25%, or 10%, respectively. We classify insurance companies by bond transaction volume in the year prior to each event. The baseline coefficients (Month = m) measure the level of the dependent variable in month m relative to month -5 for dealers unaffiliated with the issue underwriter. The interaction coefficients (Month = $m \times$ Affiliate = 1) measure the difference in month m between affiliated and unaffiliated dealers. The unit of observation for each regression is a Dealer \times Event \times Month. Each specification includes Dealer \times Event fixed effects and calendar Month fixed effects. Standard errors are clustered at the Dealer \times Event level. t -statistics are reported in parentheses. The number of stars (*) represents statistical significance at 10% (*), 5% (**), and 1% (***) .

	(1) All Clients	(2) Bottom 50% Clients	(3) Top 50% Clients	(4) Top 25% Clients	(5) Top 10% Clients
Month=-4	-0.015 (-1.49)	-0.003 (-0.85)	-0.012 (-1.37)	-0.010 (-1.38)	-0.009 (-1.62)
Month=-3	-0.030** (-2.12)	0.001 (0.13)	-0.031** (-2.48)	-0.023** (-2.15)	-0.022*** (-2.68)
Month=-2	-0.029 (-1.59)	-0.001 (-0.16)	-0.029* (-1.75)	-0.023 (-1.63)	-0.027** (-2.50)
Month=-1	-0.051** (-2.15)	0.001 (0.15)	-0.052** (-2.51)	-0.040** (-2.25)	-0.038*** (-2.75)
Month=0	0.023 (0.79)	0.014 (1.53)	0.009 (0.34)	0.007 (0.32)	-0.009 (-0.52)
Month=1	-0.090*** (-2.62)	0.003 (0.28)	-0.093*** (-3.09)	-0.077*** (-2.98)	-0.071*** (-3.52)
Month=2	-0.112*** (-2.85)	-0.001 (-0.08)	-0.111*** (-3.22)	-0.089*** (-3.03)	-0.083*** (-3.62)
Month=3	-0.105** (-2.37)	0.002 (0.13)	-0.107*** (-2.75)	-0.086*** (-2.58)	-0.082*** (-3.15)
Month=4	-0.129*** (-2.59)	-0.000 (-0.02)	-0.129*** (-2.95)	-0.104*** (-2.77)	-0.091*** (-3.11)
Month=5	-0.137** (-2.48)	-0.001 (-0.06)	-0.136*** (-2.81)	-0.111*** (-2.67)	-0.102*** (-3.17)
Month=-4 \times Affiliate=1	-0.004 (-0.15)	0.005 (0.70)	-0.008 (-0.38)	-0.010 (-0.53)	-0.008 (-0.56)
Month=-3 \times Affiliate=1	-0.029 (-1.16)	0.013 (1.58)	-0.042** (-1.99)	-0.052*** (-2.84)	-0.029** (-2.04)
Month=-2 \times Affiliate=1	-0.045* (-1.93)	0.000 (0.05)	-0.045** (-2.14)	-0.042** (-2.27)	-0.020 (-1.33)
Month=-1 \times Affiliate=1	-0.032 (-1.40)	0.002 (0.27)	-0.034 (-1.62)	-0.035* (-1.85)	-0.030** (-2.12)
Month=0 \times Affiliate=1	0.302*** (9.63)	0.016** (1.98)	0.287*** (9.99)	0.250*** (9.83)	0.209*** (10.43)
Month=1 \times Affiliate=1	-0.053** (-2.26)	0.005 (0.67)	-0.058*** (-2.75)	-0.053*** (-2.85)	-0.036** (-2.48)
Month=2 \times Affiliate=1	-0.088*** (-3.87)	0.004 (0.63)	-0.092*** (-4.54)	-0.090*** (-5.08)	-0.057*** (-4.17)
Month=3 \times Affiliate=1	-0.081*** (-3.59)	0.004 (0.53)	-0.084*** (-4.20)	-0.083*** (-4.75)	-0.060*** (-4.38)
Month=4 \times Affiliate=1	-0.077*** (-3.40)	0.012* (1.70)	-0.088*** (-4.39)	-0.085*** (-4.83)	-0.067*** (-4.82)
Month=5 \times Affiliate=1	-0.093*** (-4.13)	0.004 (0.67)	-0.098*** (-4.82)	-0.094*** (-5.31)	-0.062*** (-4.50)
Dealer \times Event F.E.	Y	Y	Y	Y	Y
Month F.E.	Y	Y	Y	Y	Y
N. Obs.	369,600	369,600	369,600	369,600	369,600
Adj. R^2	0.156	0.063	0.150	0.143	0.125

Appendix A. Measuring dealer profits and returns

A dealer may both engage in market-making activity, defined as transactions whose purpose is to earn profits from bid-ask spreads and commissions, as well as take positions as principal, defined as building speculative positions taken with the intent to profit from changes in the value of a security. Our goal is to decompose total dealer profits into market-making profits and position-taking profits. LIFO accounting matches the trades that liquidate each position with the most recent trades that built that position, thereby enabling us to identify the quick reversals that are characteristic of market-making activity (Figure A.1). In our main specification, we consider market-making trades those positions that are opened and closed within 7 days. Later in this appendix, we consider alternative thresholds (5, 10 and 15 days).

Under LIFO accounting, every transaction that moves inventory towards zero unwinds a position and thereby realizes a gain. Loss is simply negative gain, and a short position is simply negative inventory. Zero inventory is defined as the initial state of the dealer's inventory at the beginning of sample. Every time a position is unwound, a walkback procedure identifies matched transactions, i.e., the past transactions that were used to establish the position.

[Insert Figure A.1 and Figure A.2 here]

A simple example

The way this procedure works is best understood via an example. The dealer executes the following transactions, graphically shown in Figure A.2:

1. Buy 200 bonds at a price of 98.
2. Buy 100 bonds at 99.
3. Sell 200 bonds at 100. This transaction liquidates inventory, and therefore it realizes a gain or a loss. These 200 bonds are deemed to be the most recent 100 (bought at 99) plus 100 of the initial 200 (bought at 98). Total profit equals revenue ($200 \times 100 = 20,000$) minus cost ($(100 \times 98 + 100 \times 99 = 19,700)$, i.e., 300. This transaction leaves positive inventory of 100.
4. Sell 400 bonds at 97. The first 100 units are deemed to liquidate the existing inventory and

- realize a loss $(97 \times 100 - 98 \times 100 = -100)$. The remaining 300 units build negative inventory.
5. Buy 200 bonds at 96. This transaction covers a short and therefore realizes a profit of $(-200) \times 96 - (-200) \times 97 = 200$.
 6. After 7 days, buy 200 bonds at 96.5. The first 100 are deemed to cover negative inventory and realize a profit of $(-100) \times 96 - (-100) \times 96.5 = 50$. However, this profit is not counted as market-making profit because the position has been held for 7 days, and is therefore not deemed market-making activity. The remaining 100 bonds build positive inventory.

Implementation

For every transaction that unwinds a position, the walkback procedure returns four important variables:

- **Sign**, a direction indicator: +1 if dealer is buying (covering a short position), -1 if dealer is selling (liquidating a long position).
- **Matched**, the size of the position being unwound (# bonds)
- **Basis**, the LIFO book value, i.e., total expense from matched transactions. A long position has positive book value because buying incurs a positive expense; a short position has negative book value because short selling incurs a negative expense.
- **Match Timestamp**, the timestamp of the past transaction that built the position being unwound by the current transaction. If the position was built by multiple past transactions, each one has its own timestamp.

We use these variables to calculate the trading profit and to decompose it into market-making and position-taking components. Once again, an example may be helpful. The dealer executes the following transactions, graphically shown in Figure A.3:

1. Buy 3,000 bonds at 99, building a large positive inventory.
2. Over the next few weeks, gradually liquidate a total of 1,000 bonds at a price of 100.
3. A liquidity provision opportunity materializes. Buy 500 bonds for 97.5 and within the same week sell 700 bonds for 98.5. 500 of the bonds are deemed to be the same 500 that had recently been bought, realizing market-making profit of $500 \times 98.5 - 500 \times 97.5 = 500$. The

remaining 200 bonds are deemed to continue the gradual liquidation.

4. Over the next few weeks, continue to gradually liquidate inventory (800 bonds at 100).

[Insert Figure A.3 here]

As a result of these transactions, final inventory is 1,000 bonds. Since the last sell price was 100, the inventory is deemed to be worth 100,000. This is also the change in inventory, since inventory started at zero.

Total trading revenue is equal to $(-3,000) \times 99 + 1,000 \times 100 + (-500) \times 97.5 + 700 \times 98.5 + 800 \times 100 = -96,800$. Thus, total profit is equal to total trading revenue plus change in inventory value, i.e., $-96,800 + 100,000 = 3,200$. Of this, we have attributed 500 to market-making profits. The remainder, 2,700, is deemed to be position-taking profits.

First, for every transaction that unwinds a position, we define the dollar gain as

$$\text{Gain} = \text{Proceeds} - \text{Basis}. \tag{A1}$$

where Basis is given above, and

$$\text{Proceeds} = -\text{Sign} \cdot \text{Matched} \cdot \text{Transaction Price}. \tag{A2}$$

is the revenue from the transaction. When liquidating a long position, the dealer obtains positive revenue, and when covering a short position it obtains negative revenue. Next, we define

$$\text{Time Difference} = \text{Current Transaction Timestamp} - \text{Match Timestamp}, \tag{A3}$$

i.e., the time between the current date at which the position is unwound and the matched past date at which the position was built.

Then, we calculate market-making (MM) and position-taking (PT) profits:

$$\text{MM Profit} = \begin{cases} \text{Gain} & \text{if Time Difference} < 7 \text{ days,} \\ 0 & \text{otherwise} \end{cases} \quad (\text{A4})$$

$$\text{PT Profit} = \text{Net Trading Revenue} + \Delta\text{Inventory Value} - \text{MM Profit}.$$

Next, we use these profits to calculate returns. The two return measures have different denominators for reasons explained in the next subsection.

$$\begin{aligned} \text{MM Return} &= \text{MM Profit} / |\text{Basis}| \\ \text{PT Return} &= \text{PT Profit} / \text{Average Absolute Inventory}. \end{aligned} \quad (\text{A5})$$

Average Absolute Inventory is calculated as the time-weighted average of the absolute value of inventory within a week:

$$\text{Average Absolute Inventory} = \sum_{i=0}^N |\text{Inventory}_t| \cdot (t_{i+1} - t_i), \quad (\text{A6})$$

where t_i is the time at which trade $i = 1, 2, \dots, N$ is executed within the week (the time of one week is normalized to 1; $t_0 = 0$ is the beginning of the week, and $t_{N+1} = 1$ is the end of the week). For instance, if from Monday to Thursday (4 days) inventory was +140, and from Thursday to Sunday (3 days) inventory was -42, Average Absolute Inventory is equal to $4/7 \cdot 140 + 3/7 \cdot 42 = 98$. This procedure is meant to reflect the average inventory commitment per unit of time.

Calculation of returns

Our definition of returns requires some caveats. First, in calculating returns, the denominator is the absolute value of Basis (for market-making) or Inventory (for position-taking). For normal firms, return is calculated as profit divided invested capital. For a dealer, inventory is not a measure of invested capital. Instead, the dealer is likely to have to commit capital in the form of margin for both long and short positions (margin on repurchase agreements and similar arrangements, for long positions, and outright margin for short positions). Thus, we assume that committed capital is

proportional to the dollar risk taken, i.e., to the absolute dollar size of the inventory, regardless of sign. Further, because we do not want to make assumptions about the margin requirements faced by a dealer, we assume that the committed capital is simply equal to the absolute dollar inventory (i.e., a proportion of 1:1). As a result, our measure of market-making return has the correct sign and relative magnitude in a comparison across dealers, but it is likely too small in magnitude and should not be interpreted as a precise quantitative estimate of market-making returns. (Our dollar measure does not suffer from this problem).

Second, position-taking return is calculated on a standard time period (one week) and then annualized. However, market-making return is not annualized, but rather measured on a per-transaction basis. Suppose a dealer quickly buys and sells a security within one second, and then lays idle for the next 59 seconds. Annualizing returns in this case amounts to assuming that the dealer’s capital was committed only for that one second, leading to results that defy intuition.¹⁵

Arguably, even per-transaction accounting presents an incomplete view, as our measure of “returns” only captures average markup and it does not reward a dealer for achieving a higher volume. If, for a given level of capital commitment, Dealer A achieves twice the volume of Dealer B at three-quarters of the markup, our calculation shows B as the more successful dealer. A possible solution would be measuring returns on a per-time-period basis, assuming that the denominator is fixed in every time period, e.g.:

$$\begin{aligned} \text{MM Return} &= \text{Weekly MM Profit} / \text{Weekly Committed Capital} = \\ &= \sum_{t \in \text{week}} \text{MM Profit} / \sup_{t \in \text{week}} |\text{Basis}|. \end{aligned} \tag{A7}$$

However, this procedure would require an arbitrary determination of the amount of committed capital (in this example, the highest absolute level of inventory). To avoid this arbitrary determination, we use our simpler measure. On the other hand, we also present results using a dollar profits measure. This measure does not suffer from this problem, and thus takes into account potential transaction volume heterogeneity.

¹⁵A 0.1% markup obtained in one second corresponds to an annualized return of $0.1 \cdot 60 \cdot 60 \cdot 8 \cdot 252 = 725,760\%$, assuming 8 hours a day and 252 trading days a year. Using continuous compounding, the number is too large to be calculated with standard software.

Robustness

Table VII in the main text uses the returns and profits from market-making and position-taking activity calculated as described above. In particular, positions closed within 7 calendar days of opening are deemed to constitute market-making activity. Our results are not sensitive to this threshold. For robustness, we also identify market-making activity using 5-, 10-, and 15-day thresholds instead of 7 days. These results are reported in Tables A.I and A.II.

[Insert Table A.I and Table A.II here]

Figure A.1. Motivation for the use of LIFO accounting.

A dealer may engage in both market-making activity as well as take positions as principal. LIFO matches the transaction that liquidates each position with the most recent trades that built that position, thereby enabling us to identify the quick reversals that are characteristic of market-making activity.

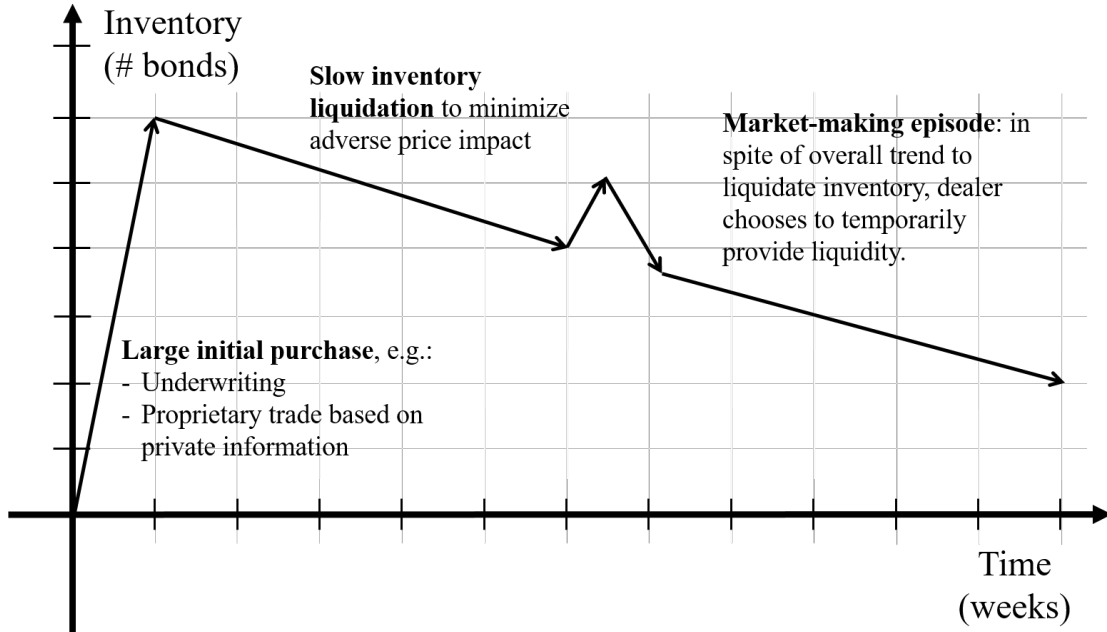


Figure A.2. Identification of transactions that realize gains and losses.

A transaction realizes a gain or a loss whenever it liquidates a position, i.e., whenever it moves inventory towards zero. Under LIFO accounting, the book value (BV) used to determine gain or loss is determined by matching each transaction that liquidates a position with the most recent transaction or transactions of opposite sign that built that position. A byproduct of this matching is the date of the matched past transactions, which permits us to determine the time elapsed between building and unwinding the position.

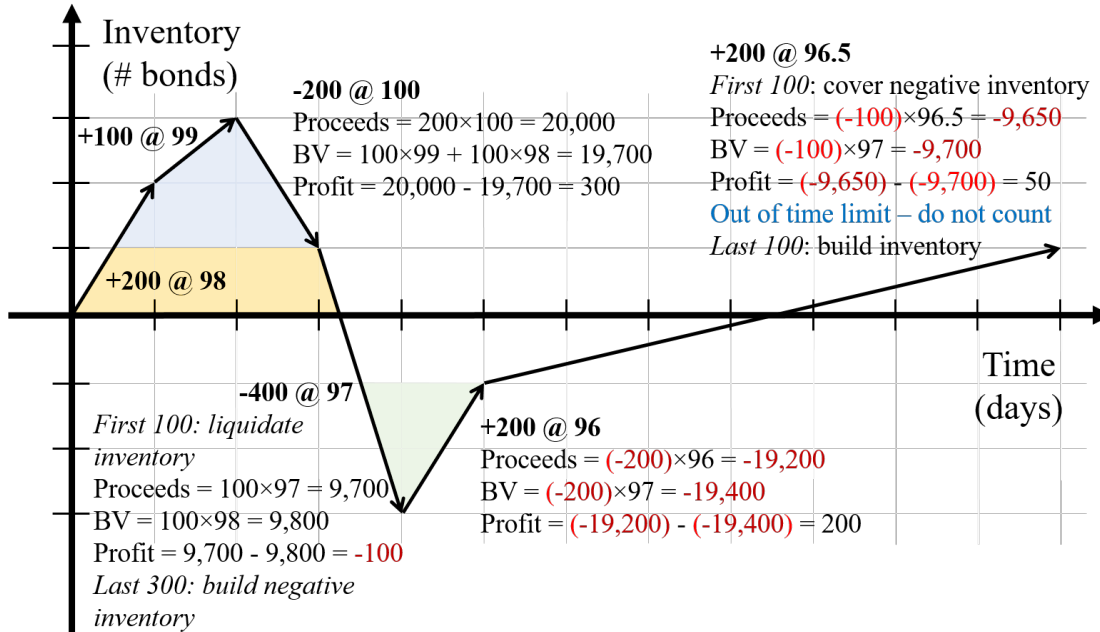


Figure A.3. Decomposition of trading profits between market-making and position-taking.

Total trading gains include net trading revenues plus gains or losses on inventory value. Under LIFO accounting, market-making profits are robust to different assumptions about initial inventory. Once market-making profits are calculated, they can be subtracted from total trading profits to obtain position-taking profits.

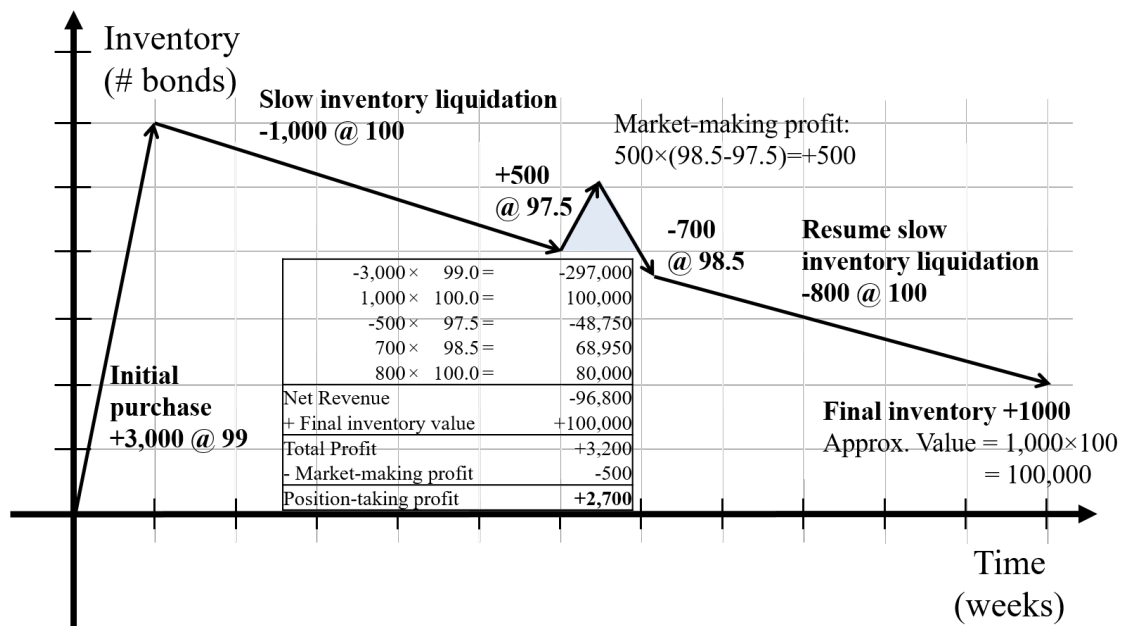


Table A.I. Alternative Thresholds for MM and PT Activity (percent specifications)

This table shows coefficient estimates from Equations (6) and (7). The dependent variable is trading returns expressed in basis points. Columns (1)–(3) are comparable to Column (2) of Table VII (market-making or MM), and Columns (4)–(6) are comparable to Column (3) of the same table (position-taking or PT). The only difference is the threshold used to identify MM activity. Table VII is estimated assuming that positions closed within 7 days of opening constitute MM activity, whereas here we use three alternative thresholds. The unit of observation for each regression is a Dealer \times Bond \times Event \times Week. Each specification includes Dealer \times Bond \times Event fixed effects and calendar Week fixed effects. Standard errors are clustered at the Dealer \times Bond \times Event level. t -statistics are reported in parentheses. The number of stars (*) represents statistical significance at 10% (*), 5% (**), and 1% (***).

	Market-Making Return			Position-Taking Return		
	(1) 5 day	(2) 10 day	(3) 15 day	(4) 5 day	(5) 10 day	(6) 15 day
Month=-4	-1.0 (-1.35)	-0.2 (-0.31)	-0.0 (-0.04)	0.7 (0.52)	0.6 (0.45)	0.5 (0.36)
Month=-3	-2.5** (-2.41)	-2.4** (-2.19)	-2.4** (-2.10)	0.4 (0.21)	0.3 (0.20)	0.3 (0.15)
Month=-2	-2.2 (-1.54)	-1.8 (-1.20)	-2.5 (-1.54)	2.5 (1.05)	2.5 (1.03)	2.3 (0.98)
Month=-1	-3.1* (-1.76)	-2.4 (-1.32)	-2.7 (-1.42)	4.5 (1.48)	4.4 (1.46)	4.3 (1.42)
Month=0	-3.4 (-1.64)	-3.6 (-1.63)	-4.4* (-1.90)	7.0* (1.87)	7.0* (1.87)	6.9* (1.83)
Month=1	-4.9** (-1.98)	-4.2 (-1.60)	-4.7* (-1.74)	4.5 (1.03)	4.5 (1.02)	4.3 (0.98)
Month=2	-5.7** (-2.02)	-5.7* (-1.88)	-6.6** (-2.08)	6.0 (1.17)	6.0 (1.16)	5.8 (1.13)
Month=3	-5.9* (-1.84)	-5.6* (-1.65)	-6.8* (-1.91)	6.2 (1.06)	6.1 (1.05)	5.9 (1.01)
Month=4	-6.2* (-1.72)	-5.7 (-1.47)	-6.3 (-1.57)	6.6 (1.01)	6.6 (1.01)	6.4 (0.97)
Month=5	-7.4* (-1.86)	-7.2* (-1.71)	-8.2* (-1.85)	9.1 (1.26)	9.1 (1.26)	8.8 (1.22)
Month=-4 \times Affiliate=1	-2.9** (-2.09)	-3.5** (-2.37)	-3.9** (-2.42)	-0.4 (-0.12)	-0.4 (-0.11)	-0.4 (-0.11)
Month=-3 \times Affiliate=1	-0.2 (-0.13)	-0.4 (-0.28)	-1.0 (-0.62)	3.4 (0.94)	3.4 (0.96)	3.3 (0.94)
Month=-2 \times Affiliate=1	-0.6 (-0.35)	-0.5 (-0.32)	-1.4 (-0.83)	2.4 (0.70)	2.6 (0.74)	2.6 (0.74)
Month=-1 \times Affiliate=1	-3.0* (-1.95)	-2.7* (-1.67)	-2.6 (-1.61)	-2.3 (-0.67)	-2.4 (-0.70)	-2.4 (-0.69)
Month=0 \times Affiliate=1	-4.9*** (-3.17)	-4.8*** (-3.08)	-5.3*** (-3.24)	10.5*** (2.86)	10.5*** (2.86)	10.4*** (2.85)
Month=1 \times Affiliate=1	-2.8* (-1.65)	-2.7 (-1.60)	-2.7 (-1.45)	2.4 (0.69)	2.6 (0.73)	2.7 (0.78)
Month=2 \times Affiliate=1	-2.5 (-1.47)	-2.8* (-1.68)	-3.0* (-1.77)	1.9 (0.54)	2.0 (0.59)	2.1 (0.59)
Month=3 \times Affiliate=1	-2.0 (-1.26)	-1.2 (-0.73)	-1.4 (-0.82)	-0.5 (-0.14)	-0.5 (-0.14)	-0.3 (-0.10)
Month=4 \times Affiliate=1	-2.5 (-1.38)	-2.8 (-1.56)	-2.8 (-1.51)	5.5 (1.58)	5.5 (1.59)	5.6 (1.61)
Month=5 \times Affiliate=1	-3.3* (-1.84)	-3.5* (-1.92)	-3.6** (-1.97)	1.0 (0.28)	1.1 (0.31)	1.1 (0.32)
Dealer \times Event \times Bond F.E.	Y	Y	Y	Y	Y	Y
Week F.E.	Y	Y	Y	Y	Y	Y
N. Obs.	1,430,215	1,736,558	1,899,795	11,336,972	11,336,964	11,336,959
Adj. R^2	0.405	0.363	0.338	0.002	0.002	0.002

Table A.II. Alternative Thresholds for MM and PT Activity (dollar specifications)

This table shows coefficient estimates from Equations (6) and (7). The dependent variable is trading profits expressed in thousands of dollars. Columns (1)–(3) are comparable to Column (5) of Table VII (market-making or MM), and Columns (4)–(6) are comparable to Column (6) of the same table (position-taking or PT). The only difference is the threshold used to identify MM activity. Table VII is estimated assuming that positions closed within 7 days of opening constitute MM activity, whereas here we use three alternative thresholds. The unit of observation for each regression is a Dealer \times Event \times Week. Each specification includes Dealer \times Event fixed effects and calendar Week fixed effects. Standard errors are clustered at the Dealer \times Event level. t -statistics are reported in parentheses. The number of stars (*) represents statistical significance at 10% (*), 5% (**), and 1% (***)

	Market-Making Profit			Position-Taking Profit		
	(1) 5 day	(2) 10 day	(3) 15 day	(4) 5 day	(5) 10 day	(6) 15 day
Month=-4	0.0*** (3.61)	0.0*** (3.79)	0.0** (2.51)	0.1 (0.02)	-0.0 (-0.01)	0.0 (0.00)
Month=-3	0.1*** (5.58)	0.1*** (5.39)	0.1*** (4.19)	4.9 (0.80)	4.7 (0.78)	4.7 (0.78)
Month=-2	0.1*** (6.40)	0.1*** (5.86)	0.1*** (4.81)	5.3 (0.63)	5.2 (0.63)	5.2 (0.62)
Month=-1	0.1*** (6.77)	0.2*** (6.32)	0.2*** (5.22)	8.6 (0.80)	8.4 (0.78)	8.3 (0.77)
Month=0	0.2*** (6.96)	0.2*** (6.62)	0.2*** (5.72)	17.0 (1.28)	16.7 (1.25)	16.6 (1.24)
Month=1	0.2*** (4.88)	0.2*** (4.78)	0.2*** (3.90)	8.4 (0.53)	8.1 (0.51)	8.0 (0.51)
Month=2	0.2*** (5.00)	0.2*** (4.87)	0.2*** (3.91)	11.8 (0.65)	11.4 (0.63)	11.2 (0.62)
Month=3	0.2*** (5.08)	0.3*** (4.87)	0.3*** (4.01)	10.8 (0.52)	10.3 (0.50)	10.1 (0.49)
Month=4	0.2*** (5.24)	0.3*** (5.04)	0.3*** (4.17)	14.2 (0.61)	13.7 (0.59)	13.5 (0.58)
Month=5	0.3*** (5.25)	0.3*** (4.98)	0.3*** (4.18)	22.7 (0.88)	22.1 (0.86)	21.9 (0.85)
Month=-4 \times Affiliate=1	0.0 (0.76)	-0.0 (-0.42)	-0.0 (-0.27)	7.2 (0.36)	7.1 (0.35)	6.8 (0.34)
Month=-3 \times Affiliate=1	-0.0 (-0.13)	-0.1 (-0.94)	-0.1 (-1.07)	17.1 (0.86)	16.9 (0.86)	17.3 (0.87)
Month=-2 \times Affiliate=1	-0.0 (-1.04)	-0.1* (-1.65)	-0.1 (-1.12)	3.7 (0.19)	3.0 (0.16)	2.6 (0.14)
Month=-1 \times Affiliate=1	-0.0 (-1.09)	-0.1 (-1.33)	-0.0 (-0.64)	0.5 (0.02)	-0.4 (-0.02)	-0.4 (-0.02)
Month=0 \times Affiliate=1	0.4*** (6.93)	0.3*** (4.94)	0.4*** (4.76)	29.9 (1.51)	29.0 (1.46)	28.4 (1.43)
Month=1 \times Affiliate=1	-0.2*** (-4.83)	-0.3*** (-4.55)	-0.3*** (-3.82)	30.8 (1.60)	30.8 (1.60)	30.9 (1.61)
Month=2 \times Affiliate=1	-0.2*** (-4.49)	-0.3*** (-4.61)	-0.3*** (-4.21)	-15.3 (-0.82)	-15.6 (-0.83)	-15.1 (-0.81)
Month=3 \times Affiliate=1	-0.2*** (-4.45)	-0.3*** (-5.10)	-0.3*** (-4.62)	10.8 (0.56)	10.6 (0.55)	11.0 (0.56)
Month=4 \times Affiliate=1	-0.2*** (-4.20)	-0.3*** (-4.19)	-0.3*** (-3.83)	20.0 (1.06)	19.5 (1.03)	19.1 (1.00)
Month=5 \times Affiliate=1	-0.2*** (-5.05)	-0.4*** (-6.10)	-0.4*** (-5.79)	-7.6 (-0.41)	-7.2 (-0.38)	-7.0 (-0.37)
Dealer \times Event F.E.	Y	Y	Y	Y	Y	Y
Week F.E.	Y	Y	Y	Y	Y	Y
N. Obs.	4,466,647	4,465,301	4,464,533	4,410,778	4,410,778	4,410,778
Adj. R^2	0.129	0.112	0.095	0.005	0.005	0.005

Appendix B. An example of language in an offering prospectus

The following is an excerpt of standard language taken from a 2012 bond offering prospectus (our emphasis):

“[The issuer] has been advised by the underwriters that they presently intend to make a market in the notes of each series after completion of this offering. [...]

In connection with this offering, the underwriters may purchase and sell the notes of *any series* in the open market. These transactions may include short sales and purchases on the open market to cover positions created by short sales. [...] A short position is more likely to be created if the underwriters are concerned that there may be downward pressure on the price of the notes of such series in the open market after pricing that could adversely affect investors who purchase such notes in this offering.

Similar to other purchase transactions, the underwriters’ purchases to cover their short sales may have the effect of raising or maintaining the market price of the notes of the applicable series or preventing or retarding a decline in the market price of such notes. As a result, the price of such notes may be higher than the price that might otherwise exist in the open market.”

This excerpt is interesting for two reasons. First, it is evidence that underwriters explicitly plan to support the price of other securities beside the security being issued, specifically by taking actions that may affect the open market price of these securities. Second, it describes a strategy (short-selling and then covering the shorts) which we have unsuccessfully tried to document. Although covering shorts may be consistent with aggressive bidding, there is no evidence that the average underwriter-dealer establishes significant short positions in the first place.