Life after Default: Dealer Intermediation and Recovery in Defaulted Corporate Bonds

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Abstract

Despite their high-risk profile and low likelihood of repayment, U.S. corporate bonds remain actively traded after default. We document that upon default intermediation shifts to dealers with prior expertise in trading the bond. These primary dealers locate higher-valuation counterparties, participate in longer intermediation chains, absorb more order flow in their inventory, and provide more efficient pricing than other dealers. The switch to trading with primary dealers raises recovery rates by 10%. Our results highlight the importance of dealers' expertise, coupled with their ability to connect with specialized investors, which contributes to stabilizing distressed bond markets and mitigating corporate credit risk.

JEL Classification: G12, G14, G24

Keywords: corporate default, corporate bonds, recovery rates, over-the-counter markets, dealer networks

Corporate bonds are traded in decentralized over-the-counter (OTC) markets through dealers who have special trading skills and expertise in searching for counterparties, assessing counterparties' willingness to pay, and taking bonds into inventory (Duffie, Garleanu, and Pedersen, 2005; Goldstein and Hotchkiss, 2020; Glode and Opp, 2016; Glode and Opp, 2019; Hugonnier, Lester, and Weill, 2019; Colliard, Foucault, and Hoffmann, 2021; Sambalaibat, 2022; Chaderina and Glode, 2023). The dealers' skills become particularly important for trading and pricing corporate bonds at times of distress. In normal times, insurers and pension funds are the largest investors in corporate bonds with a preference to buy and hold (Koijen and Yogo, 2023). However, when corporate bonds default their natural holders change due to the altered investment characteristics and risk profile of the bonds and the need for collective action in default proceedings (Ivashina, Iverson, and Smith, 2016).[1] Corporate distress events therefore provide a setting in which dealer expertise matters for consolidating ownership and transitioning from one group of investors to another thus affecting the pricing of corporate debt beyond the heightened cash-flow risk.

Using hand-collected data on 2,425 distinct U.S. defaulted corporate bonds issued by 498 unique U.S. firms we show that a primary dealer-type system has emerged in the corporate bond market without any government intervention or regulation. Primary dealers are intermediaries who possess the expertise required for providing liquidity and facilitating trading activity in a particular bond on the secondary OTC market. The designation of a primary dealer is most commonly associated with government bond markets that are often referred to as "primary dealer markets".[2] However, primary dealers play a crucial role in

[1] Based on eMAXX data, the ownership share of traditional institutional investors, mostly mutual funds, declines on average from 25% pre-default to 12% post-default. When the issuing company fails to meet its contractual obligations, the default event triggers a series of negotiations between bondholders and the issuer that requires specialized expertise and often leads to court enforcement for which mutual funds are unwilling and unsuited. In many default cases, a creditors' committee is formed or a trustee is appointed that represents the interests of bondholders during the recovery process and negotiates on their behalf to maximize the recovery for bondholders which hedge funds specialize on.

[2] In the government bond market, the primary dealer, or primary market maker designation signifies that this dealer was likely involved in the original issuance of the bond in the primary market and has

smoothing the flow of trading and liquidity in the corporate bond market as well. In the defaulted corporate bond setting, we identify one unique primary dealer for each bond endogenously. We designate the dealer that intermediates the largest number of trades in the bond during the year prior to default as the primary dealer in that bond. Primary dealers handle on average 17% of the order flow prior to a bond's default, making them bond-central and allowing them to develop expertise in that particular bond. Sometimes but not always the primary dealer is the bond's underwriter or a major dealer who is central to the entire corporate bond network. The bond's primary dealer is, however, generally distinct from the most central dealer(s) in the overall dealer network and, as we show, plays a special role in intermediating the bond once it defaults. We find that the dealers' intermediation network adjusts to handle the abnormal trading activity and accommodate the shift in ownership when trading volume in the firm's bonds spikes during a corporate default. Bonds in good standing are intermediated by many dealers. After the default, the non-primary dealers cut back their intermediation of defaulted bonds and the primary dealer picks up the slack by intermediating up to 40-50% of the turnover in a defaulted bond.

This reorganization of liquidity provision in the OTC corporate bond market increases trade-level recovery rates by \$6.79 per each \$100 invested and average recovery rates by \$4.67 per each \$100 invested percentage points when trades are routed via primary dealers. These extra recoveries are equivalent to a more than 10% premium over the mean recovery rate. The recovery rate premium by primary dealers is important as it mitigates credit risk for investors ex-ante. We confirm our univariate and multivariate estimates using several instrumental variables approaches at the trade and bond level.

The literature offers several potential explanations for why primary dealers who are more familiar with the defaulted bond provide better recoveries than other dealers. One explana-

continued to be a prominent participant in the secondary market for that bond. The U.S. Treasury market has a well-established primary dealer system. Primary dealers are financial institutions authorized by the U.S. Department of the Treasury to participate directly in the auctions of Treasury securities.

tion is that, consistent with the models of Glode and Opp (2019), Hugonnier, Lester, and Weill (2019), Sambalaibat (2022), and Chaderina and Glode (2023), primary dealers possess endogenous trading skills and superior expertise in intermediating the defaulted bond. Trading with a primary dealer then results in better allocation efficiency leading to better recovery rates. Asymmetric information about the residual value of the bondholders who are subordinated claimholders rises after the default. Glode and Opp (2016) show that longer intermediation chains weaken traders' incentives to screen counterparties thus reducing the adverse selection and increasing trade efficiency. An alternative explanation of our findings is that primary dealers switch to riskless principal trades after the default and are capable of brokering trades at lower cost and, hence, better prices (Bao, O'Hara, and Zhou, 2018; Li and Schürhoff, 2019; Goldberg and Nozawa, 2021). Yet another explanation is that primary dealers may have lower inventory costs and can pass some savings to buyers as price improvements (Bessembinder, Jacobsen, Maxwell, and Venkataraman, 2018).

To test these explanations we use granular transaction data and dealer identifiers from TRACE to construct the intermediation chains and client-to-dealer, dealer-to-dealer, and dealer-to-client trading networks and quantify dealers' inventory risk-taking. We find that consistent with the model of Glode and Opp (2016) intermediation chains are 7% shorter for primary dealers before the default but that they are 11% longer for primary dealers than for other dealers post-default. We next examine primary dealers' tendency to take bonds into inventory as opposed to prearranging trades in defaulted bonds in the role of a broker. We consider trades denoted as agency trades in TRACE and principal trades that are offset within one minute as agency trades. We find that dealers are significantly less likely to act as brokers once a bond defaults. This highly economically and statistically significant effect suggests dealers take recently defaulted bonds and the associated risks on their own balance sheets and keep them overnight rather than searching for a willing buyer first. We further find that primary dealers more readily risk their own capital for intermediating defaulted bonds for which they had handled most of the order flow prior to default and that primary dealers are even more likely to act as principals once a bond defaults.

To check that dealer expertise is tantamount to higher recovery, we investigate how trading with primary dealers affects price rebound after default. Using OLS and IV approaches, we find that investors who sell to primary dealers immediately after default forgo \$5.62 per \$100 bond's par value less than investors who sell immediately after default to other dealers forgo, as compared to holding the bond until the second month after default. Thus, selling to primary dealers immediately after default effectively counterbalances temporary price pressures, given that the subsequent price rebound is less pronounced for the trades routed via primary dealers. When combined with the results on recovery rates, our findings show that trading with a primary dealer leads to higher and more stable recovery prices after default vis-à-vis prices observed once the initial default surprise has vanished. Our findings also suggest that the recovery benefits provided by primary dealers during default-induced times of stress are permanent. This is consistent with being the result of primary dealers' superior expertise and not due to alternative explanations such as fire sale discounts, price pressures, and market timing. Overall, the evidence suggests that primary dealers stabilize distressed bond markets by offering higher, more stable, and informationally efficient prices than other dealers, which mitigates credit risk for existing investors.

More generally, our study highlights that corporate bond market structure evolves endogenously. After the bond's default event, investors switch to trading with primary dealers who locate higher-valuation investors, some of whom specialize in distressed products or act as opportunistic investors who are willing to pay higher prices as the ownership share of traditional institutional investors drops from 25% pre-default to 12% post-default. Thus, primary dealers provide an exit for investors facing selling pressure by taking on inventory risk with bonds they are familiar with. Moreover, they are capable of locating new investors more effectively than other dealers, albeit through longer intermediation chains.

Literature overview. Our paper is related to several strands of literature. We explore corporate bond default events as a shock to the need for intermediation and document the response of OTC markets previously studied in other contexts, including rating downgrades (May, 2010; Ellul, Jotikasthira, and Lundblad, 2011; Bao, O'Hara, and Zhou, 2018), bond index exclusions (Dick-Nielsen and Rossi, 2019) and corporate bond mutual fund redemptions (Goldstein, Jiang, and Ng, 2017; Choi, Hoseinzade, Shin, and Tehranian, 2020). Few studies make use of trading data in defaulted bonds. Ivashina, Iverson, and Smith (2016) and Feldhütter, Hotchkiss, and Karakaş (2016) examine the link between pre-default bond trading and the concentration and value of debt claims. Demiroglu, Franks, and Lewis (2022) investigate how transparency of defaulted bond prices impacts wealth transfers between different classes of creditors in Chapter 11. While their study considers price transparency, we highlight an important mechanism for the functioning of the bond market and market participants' trading behavior in defaulted bonds. Nagler and Ottonello (2023) provide a complementary view on how bond market liquidity and corporate financial actions are intertwined.

We also contribute to the literature exploring the role of dealer networks in OTC markets. Di Maggio, Kermani, and Song (2017), Li and Schürhoff (2019) and Hendershott, Li, Livdan, and Schürhoff (2020) explore network-based explanations for the emergence of trades and trade outcomes. Colliard, Foucault, and Hoffmann (2021) reconcile dealer inventory management with network frictions and the position of dealers within the dealer network. We highlight the role of primary dealers for defaulted bond intermediation and demonstrate the counterbalancing effects of primary dealers on depressed prices of recently defaulted bonds.

Our study is related to the broader literature on implications of OTC search and bargaining frictions, such as Duffie, Garleanu, and Pedersen (2005) and Feldhütter (2012), as well as Bessembinder, Maxwell, and Venkataraman (2006), Edwards, Harris, and Piwowar (2007), and Goldstein, Hotchkiss, and Sirri (2007). Our findings show that trade outcomes differ for investors depending on their dealer selection and dealers' prior experience with a defaulted bond. We also capture the implications of bond pricing models (Friewald and Nagler, 2019) and complement the literature on OTC dealer capital commitment and liquidity provision. Bao, O'Hara, and Zhou (2018), Bessembinder, Jacobsen, Maxwell, and Venkataraman (2018), Dick-Nielsen and Rossi (2019), Goldstein and Hotchkiss (2020), Goldberg and Nozawa (2021), and Colliard, Foucault, and Hoffmann (2021) study dealer inventory management in OTC intermediation. Our study highlights the role of primary dealers in liquidity provision by absorbing excess supply in defaulted bonds through their inventory.

Finally, we offer a novel perspective on the determinants of defaulted bonds' recovery rates. The recovery rate is usually explained by fundamental drivers such as bond and firm characteristics, as well as macroeconomic conditions (Acharya, Bharath, and Srinivasan, 2007; Bruche and Gonzalez-Aguado, 2010; Nazemi and Fabozzi, 2018). Altman, Brady, Resti, and Sironi (2005) and Jankowitsch, Nagler, and Subrahmanyam (2014) consider observable market dynamics of defaulted debt securities, such as aggregate supply and demand indicators, as well as liquidity proxies. Our study illustrates the link between the OTC market mechanism and recovery rates. While previous studies consider average recovery rates per bond, we explore a new approach that captures the heterogeneity of recovery prices across different investors which provides insights into the risks associated with defaulted bonds. Finally, we document post-default price rebound as a measure of price efficiency.

The paper is organized as follows. Section 1 describes the data and documents dealer intermediation in defaulted bonds. Section 2 quantifies the impact of dealer intermediation on recovery rates. Section 3 explores the role of primary dealers in trading defaulted bonds. Section 4 documents price efficiency during default. We conclude in Section 5.

1 Default Data and Intermediation of Defaulted Bonds

This section describes the data sources used in our empirical analysis and the sample filters to clean the data. We first create the sample of defaulted corporate bonds by combining several data sets, defining pre- and post-default trading periods, and providing descriptions of the explanatory variables used in our analysis. We then construct the dealer network in defaulted bonds, identify the defaulted bonds' primary dealer(s), and document the intermediation of defaulted bonds.

1.1 Default events and data sources

To create the sample of defaulted bonds, we start by hand-collecting data on defaulted bonds and their default dates based on two approaches, since no comprehensive default database is widely available. First, we consider the Mergent Fixed Income Securities Database (FISD), Moody's Default & Recovery Database through monthly data tables available via Moody's Investor Service, and S&P Capital IQ fixed-income data to identify and retrieve information about U.S. corporate bond default events during the years 2004-2016.[3] These data sources yield observations associated with three types of corporate default events: Chapter 11 (both reorganizations and liquidations), Chapter 7 liquidations, and distressed exchanges. Second, we follow Jankowitsch, Nagler, and Subrahmanyam (2014) and consider rating downgrades to the two worst possible rating categories for which we utilize comprehensive historical rating information by the rating agencies Moody's, S&P, and Fitch Ratings retrieved from FISD. The two rating-based default events are downgrades to the second worst rating class, e.g., S&P's C rating, representing unlikely-to-pay events or situations in which formal default is considered inevitable but has not yet taken place, and downgrades to the worst rating class,

[3] The sample period ends in 2016 due to data limitations imposed by the availability of all data sources.

e.g., S&P's D rating, representing actual formal defaults.[4] To capture a bond's default as a single event in our analysis, we select the first default date for a bond and eliminate from our sample all consecutive default events observed within one year.[5]

We apply several data filters to our sample of defaulted bonds. To be included in our analysis, a defaulted bond needs to have basic firm- and bond-specific information in FISD, such as issuer identity and bond seniority. It also needs to be in the Transaction Reporting and Compliance Engine (TRACE) for determining a recovery rate based on transaction prices within the 30-day period immediately after default and to match default events to pre- and post-default transactions. We match the defaulted bonds to FISD and TRACE data based on the bonds' CUSIP identifiers. Following this procedure, we identify 2,636 unique U.S. corporate bond default events. The default events reflect defaults of 2,425 distinct bonds issued by 498 unique firms. A total of 182, or 7.5% of bonds default more than once.[6]

Our transaction data is from Academic Corporate Bond TRACE Data, provided by FINRA. The data allows us to track trading volume, terms of trade, and the direction of flows between dealers and investors, to whom we also refer as the dealers' clients. We

[4] Eliminating downgrades to the second lowest rating (e.g., S&P's C rating) from our sample does not materially affect our findings. Although these downgrade events do not represent actual default, they have comparable implications for buy-and-hold bond investors. For example, rating agencies define the second lowest rating class as *"default or default-like process has begun"* (Fitch Ratings, https://www.fitchratings.com/products/rating-definitions) or *"likely in, or very near, default, with some prospect of recovery"* (Moody's, https://ratings.moodys.com/rating-definitions). We further observe that these events yield an even lower recovery than distressed exchange events.

[5] Collecting default events from the various data sources can yield different default dates for some of the bonds. For example, one data source may report a rating downgrade to S&P's C rating which occurs weeks before a downgrade to S&P's D rating or a bankruptcy filing. All these observations are likely to refer to the same default event. To represent a bond's unique default event in our analysis as a single observation, we ignore all reported consecutive default dates of a bond that occur within one year after the first default date was observed. After the one-year time lag, a consecutive default observation will be considered a new default event, and the procedure repeats. This approach accounts for consecutive default events of a given bond when it was reinstated following the initial default event.

[6] We take a similar approach in creating the set of defaulted bonds as Jankowitsch, Nagler, and Subrahmanyam (2014). Our approach differs in that we consider only a bond's first default date as a default event and allow consecutive defaults only after a one-year time lag. With our methodology, we count about 1.1 default events per bond over the 13-year period examined in this study. Jankowitsch, Nagler, and Subrahmanyam (2014) consider several different default events for a bond even if they occur simultaneously or within a few days, and count about 2.7 default events per bond over the 8-year period that they analyze.

match the default events with transaction data from TRACE in a 365-day window prior to default as the pre-default period during normal times, and a 30-day window subsequent to default. We define the default day as the event date and the 30 days subsequent to it as the post-default period during which we expect investors' and dealers' trading decisions to be affected by the default event, given the default's surprise character. This definition is supported by the findings of Jankowitsch, Nagler, and Subrahmanyam (2014) who show that trading prices during the 31st to 90th day after default already differ significantly from the 30 days immediately after default.[7] The 30-day period for measuring default event-driven OTC trading patterns is in line with related event studies on bond market reactions.[8] The sample for comparing the pre- and post-default time periods comprises a total of 2,271,772 transactions in 2,636 defaulted bonds. Thereof, 1,956,480 bond transactions occur within the pre-default period corresponding to an average of about 740 individual trades per defaulted bond, and a total of 315,292 bond transactions occur on the default date and within the post-default period corresponding to 130 trades per defaulted bond.

Figure 1 illustrates trading patterns around default. Trading volume increases as the default event approaches. During days -30 to -1 before default, the average number of daily trades rises to an average of about 30 trades on the default day as illustrated in Figure 1, indicating that the default event is not fully anticipated by market participants. What is also interesting is that trading activity is elevated for an extended period after default and, while it reverts back to its pre-default level, defaulted bonds remain actively trading even 30 days after default.

We utilize information on the pre-default bond ownership structure from Refinitiv eMAXX

[7] The choice of a 30-day period is further supported by the possibility to resolve default events timely after default. E.g, emergence from bankruptcy can be achieved in as little as 45–60 days in prepackaged Chapter 11 cases. Time to completion may be also short in distressed exchange events, as exchange offers have to be kept open for a minimum of 20 days, according to Rule 14e-1 of the Securities Exchange Act of 1934.

[8] Ellul, Jotikasthira, and Lundblad (2011) use a 5-week period and Bao, O'Hara, and Zhou (2018) use a 1-month period in their empirical studies on market reactions to corporate bond rating downgrades.

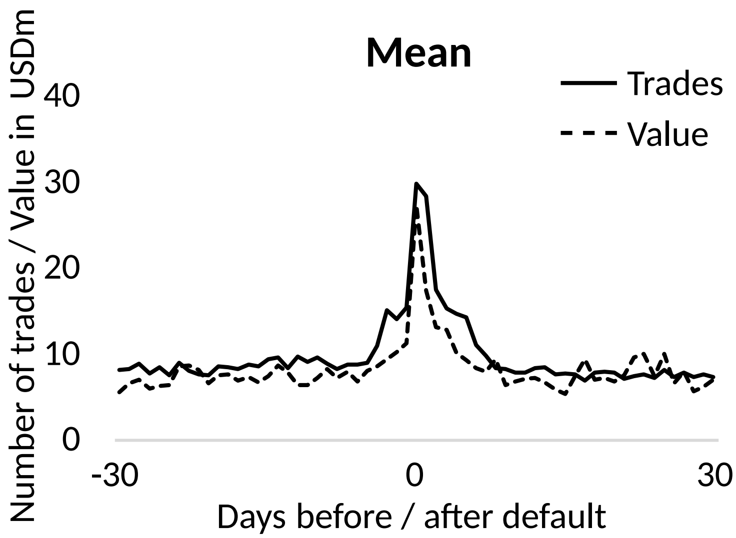

Figure 1: **Trading activity before and after default.** Average daily bond trading volume of 2,636 defaulted bonds during 30 days before and after default. Average daily volume is shown as the number of trades and total trading par value in USDm.

to construct shocks for our instrumental variable approaches. For the empirical analysis, we consider additional explanatory variables well-established in the literature to control for alternative channels. We rely on data from FISD and S&P Capital IQ for firm-, industry-, and bond-specific data. Macroeconomic data is retrieved from the Federal Reserve Economic Database of the Federal Reserve Bank of St. Louis (FRED). We replicate several bond liquidity measures using the defaulted bonds' transaction data reported to TRACE. We provide additional details on the explanatory variables in Appendix A.

1.2 Primary dealers and defaulted-bond dealer network

Masked dealer identifiers in Academic Corporate Bond TRACE data allow us to identify dealers' exposure to intermediation in individual bonds and create bond-specific trading networks. A given bond is traded by many dealers in our sample but some dealers handle the majority of the bond's order flow. These dealers are *bond-central* or *primary*. Primary dealers are important since they have expertise in trading a bond. Such expertise includes the superior ability to locate, place, and price the bond and need not be the bond's underwriter or a central dealer in the entire corporate bond dealer network.

We define the *primary dealer* for each defaulted bond as a dealer handling the largest share of trading in the bond during the year prior to default. We use all client-to-dealer transactions during the year prior to default to measure each dealer's share of trading. The primary dealers in our data handle on average 19% (median 12%) of the pre-default order flow in a given bond, dispersed between 5% of all trades at the first quartile and 25% at the third quartile. Of all dealers identified in the sample, 194 dealers served as primary dealers in at least one or more defaulted bonds, that is, having intermediated the highest number of trades among all dealers in a given bond prior to default. While many primary dealers are the primary dealers in just one or a few bonds, 43 of the 194 primary dealers are primary dealers in at least 10 different defaulted bonds.

Following the approach in Li and Schürhoff (2019), we create a corporate bond inter-dealer network based on dealer-to-dealer transactions reported to TRACE. We describe the TRACE data, data cleaning, and preparation of the dealer network in more detail in Appendix A. Figure 2 shows a representation of the dealer network as a directed graph, based on all inter-dealer transactions covered within the data sample. The network illustrates whether two dealers (nodes) have executed buy or sell transactions (links) with one another and represents all 3,383 dealers that maintain trade relationships with other dealers, based upon 44,065,910 inter-dealer transactions. In Figure 2, the majority of both primary dealers and other dealers that intermediate recently defaulted bonds are located within the periphery of the network's core. The top primary dealers are highlighted as triangles. The remaining defaulted-bond dealers are highlighted as cross marks.

In addition to the primary dealer feature, we characterize dealers' centrality for defaulted bonds as controls formally by considering eight commonly used centrality measures to reflect the centrality of dealers within the network: degree, in-degree, out-degree, eigenvector

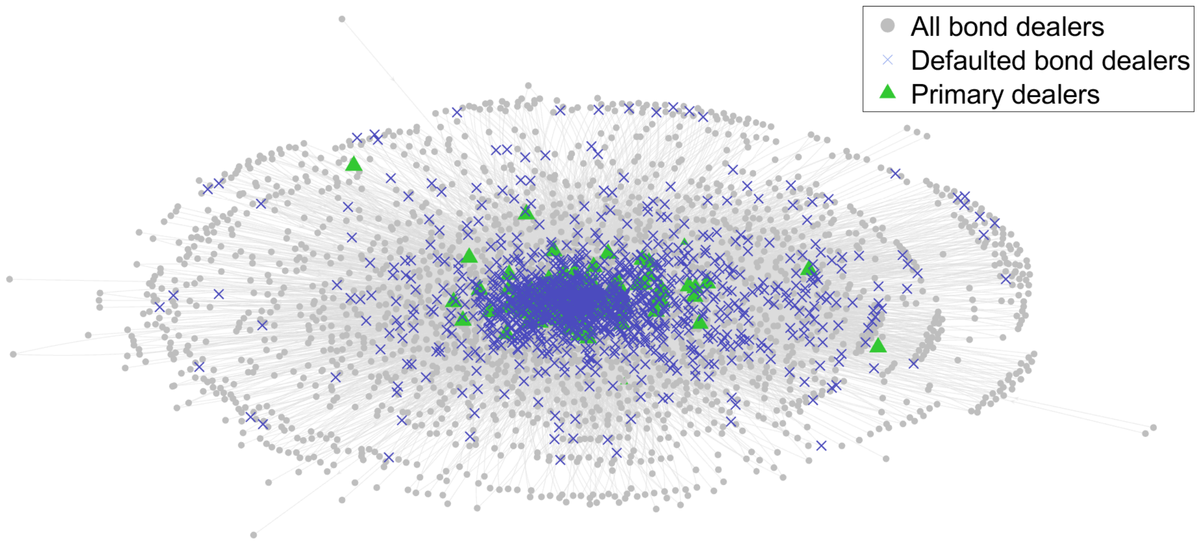

Figure 2: **Dealer network before and after default.** The figure illustrates the defaulted-bond dealer network, representing 44,065,910 inter-dealer transactions. Nodes represent the 3,383 bond dealers and links indicate trade relationships between two dealers via bond transactions reported to TRACE. The visualization of the network is performed by a force-directed algorithm that creates attractive forces between neighboring nodes and repulsive forces between distant nodes. Dealers that intermediate bonds within 30 days after a bond's default event are shown as cross marks. Primary dealers that handle most of the pre-default order flow of a bond are shown as triangles. Primary dealers and other defaulted-bond dealers are located around the periphery of the network's core.

(Bonacich, 1972), betweenness (Freeman, 1977), closeness, as well as in-closeness and out-closeness (Bavelas, 1950). We compute these measures both for (i) an equal-weighted dealer network which solely indicates the existence of a transaction relationship between two dealers and for (ii) an alternative dealer network in which links are weighted by the number of transactions executed between dealers.

Figure 3 illustrates the empirical distribution of dealer centrality among primary and non-primary dealers in the dealer network over the full sample period. The figure shows that dealers intermediating defaulted bonds are different from the average dealer; they are more central than the average dealer. Primary dealers in particular, while not the most central core dealers, tend to be more central than the average dealer in defaulted bonds.[9]

[9] A dealer within the network's core belongs to the group of the 19 most central dealers that cumulatively account for more than 25% of all corporate bond inter-dealer trading volume reported to TRACE.

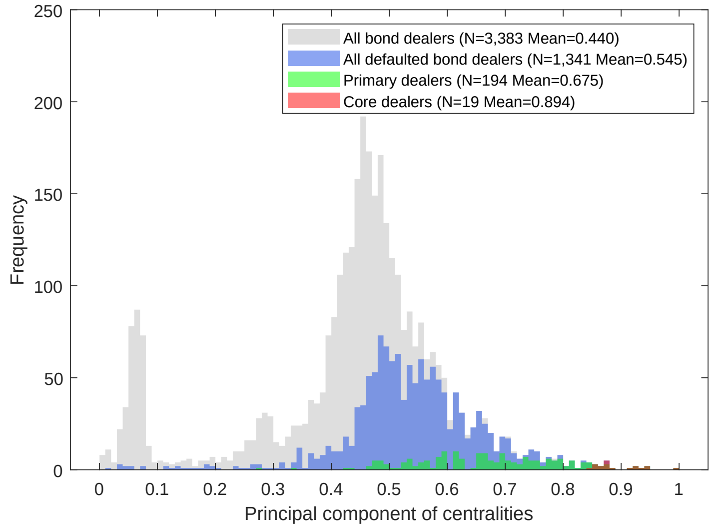

Figure 3: Empirical distributions of dealer centralities within the equal-weighted dealer network. Centrality is scaled on the interval [0,1].

In the Appendix, Table A.1 provides additional statistics on dealer centrality. Irrespective of which centrality measure is considered, the observed patterns are consistent with the core-periphery structure of dealer networks described in the literature (Di Maggio, Kermani, and Song, 2017; Hollifield, Neklyudov, and Spatt, 2017; Li and Schürhoff, 2019), as the majority of dealers bear low-rank centralities and are located at the periphery, while few dealers are placed at the core and have high centralities. For the empirical analysis, we implement monthly 1-year trailing dealer networks to capture the network structure timely before default and to account for time variation in the dealer network.[10]

1.3 Intermediation of defaulted bonds

Investors faced with a bond's default need to assess whether to keep or sell their holdings to specialized distressed and other opportunistic investors willing to hold defaulted bonds. This

[10] We rely on monthly 1-year trailing networks rather than one time-invariant dealer network over the full data sample for two reasons. First, we avoid including network information not available at the time of default. Second, although the time variation in the dealer network is limited, we thus account for network changes over time. E.g., one major bond dealer ceased to exist during the financial crisis.

section examines bond trading before and after bond default and documents intermediation chains and how default affects them. We will show that investors are more likely to sell defaulted bonds to primary dealers after default than before, that is, they trade through dealers who are experts in handling the defaulted bond.

We begin by examining trading behavior in corporate bonds before and after defaults and link it to dealers' identities as primary dealers. Based on eMAXX data, the ownership share of traditional institutional investors, mostly mutual funds, declines on average from 25% pre-default to 12% post-default. When these and other investors decide to sell bonds, they approach dealers, facing a trade-off between execution speed and transaction costs. Dealers themselves face the challenge of locating buyers within the opaque OTC market. Li and Schürhoff (2019) show that central dealers in the municipal bond dealer network provide faster but costlier trade executions. To be able to provide liquidity in defaulted bonds, dealers must provide sales channels to specialized vulture investors or commit their own balance sheets. Investors who have less access to prime brokers that cater to large institutions (Glode and Opp, 2016) need to locate specialized dealers within the dealer network that are capable of intermediating the distressed securities.

Table 1 provides summary statistics of pre- and post-default dealer intermediation for customer-to-dealer trades on the bond and transaction levels. On the bond level, we observe a significantly lower number of dealers intermediating client-to-dealer ($C2D$) trades after default than prior to default. On average 30 individual dealers are involved in $C2D$ trades for a given bond before default, but only about 11 dealers buy the bond from clients after it defaults. We further observe that dealer concentration, measured by the Herfindahl–Hirschman index of the dealers involved in $C2D$ trades, increases significantly from 0.2 pre-default to 0.39 after default. Overall, these statistics highlight a shift in bond trading after it defaults, with a decrease in the number of dealers and increased concentration in the hands of fewer dealers. We continue by considering individual $C2D$ transactions.

Table 1: **Customer-to-dealer trading summary statistics.** A total of 625,548 (494,050 pre-default and 131,498 post-default) client-to-dealer ($C2D$) trades are considered. *# of C2D dealers* is the number of individual dealers that buy a given bond from clients before and after default. *C2D dealer concentration* is the bond-specific Herfindahl–Hirschman index of the intermediating dealers, based upon the number of client-to-dealer trades. The *primary dealer* is the dealer that has executed the highest number of trades in a given bond during the year prior to default. *Broker role* indicates whether the dealer acts as a broker in a given trade. *Intermediation chain length* is the number of intermediating dealers in a client-to-client intermediation chain that is successfully executed intra-day. Significance is denoted *** (1%), ** (5%), and * (10%).

	Mean		Post		# observations	
	pre-default	post-default	minus Pre	t-stat.	pre-default	post-default
			Bond-level statistics			
# of C2D dealers	29.57	11.27	-18.298***	25.91	2,364	2,364
C2D dealer concentration	0.20	0.39	0.187***	-24.31	2,364	2,364
			Trade-level statistics			
Primary dealer	16.6%	31.2%	0.146***	-105.74	494,050	131,498
Broker role	31.6%	23.9%	-0.077***	56.70	494,050	131,498
thereof primary	31.7%	6.4%	-0.252***	124.62	82,020	41,064
thereof non-primary	31.6%	31.9%	0.003*	-1.82	412,030	90,434
Intermediation chain length	1.63	1.71	0.080***	-10.15	124,438	19,349
thereof primary	1.37	1.74	0.368***	-16.32	20,226	1,774
thereof non-primary	1.68	1.71	0.027***	-3.20	104,212	17,575

Table 1 shows that primary dealers almost double their market share in post-default bond trading, intermediating about 31% of all client-to-dealer trades, compared to less than 17% prior to default with the net difference being statistically significant at the 1%-level. We then examine whether the dealers' role as brokers and intermediation chain lengths differ before and after default, focusing on the intermediation via primary dealers vis-à-vis non-primary dealers. Overall, dealers intermediate fewer trades as brokers after the bond's default event, executing about 24% of the post-default trades as brokers versus about 32% prior to default. However, this decline is mostly due to primary dealers, who only intermediate about 6% of post-default trades as brokers. In contrast, the percentage of $C2D$ trades as brokers does not change materially from pre- to post-default trading for non-primary dealers.

Table 1 also shows that the intra-day intermediation chain length, measured by the num-

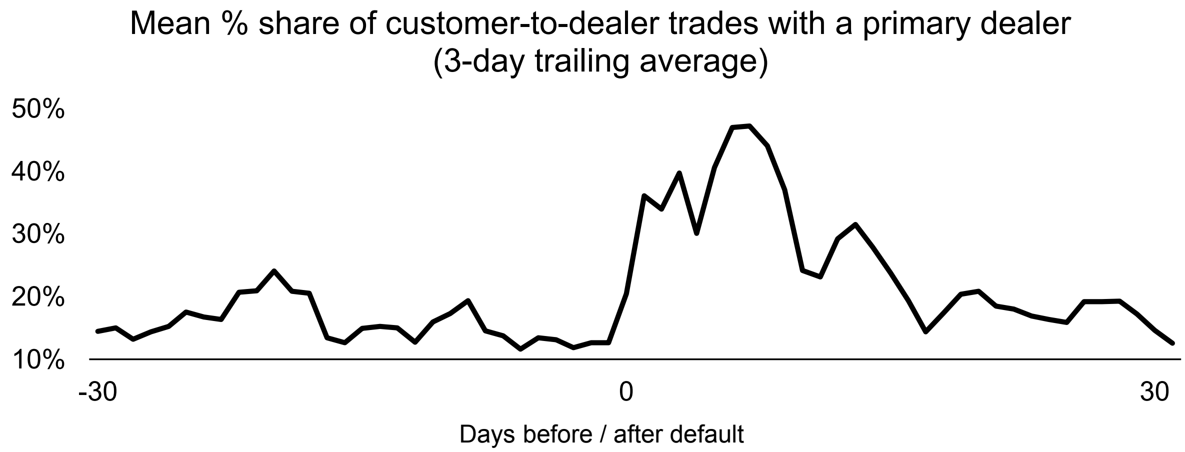

Figure 4: Share of trades with primary dealers as a percentage of the total number of customer-to-dealer trades, 3-day trailing average.

ber of dealers intermediating the bond, increases significantly from about 1.63 dealers prior to default to about 1.71 dealers after default. The intra-day intermediation chain length increases mainly due to chains initiated by a client's sale to a primary dealer. Intermediation chains that start with primary dealers increase from 1.37 dealers pre-default to 1.74 dealers post-default, whereas intermediation chains initiated by selling to non-primary dealers increase only slightly from 1.68 dealers pre-default to 1.71 dealers post-default. Overall, these statistics show that the intermediation of defaulted bonds changes after default and that these changes are primarily due to the intermediation switching to primary dealers.

We start with a simple univariate exercise illustrating the intermediation of defaulted bonds by primary dealers around the default event. To do this, we closely track customer-to-dealer trades and the intermediating dealer in each bond and calculate the percentage share of trades intermediate by primary dealers 30 days before and after the default event. Figure 4 shows that about 10%–20% of customer-to-dealer trades are intermediated by primary dealers during days immediately before default. Right after default, the percentage share of trades intermediated by primary dealers surges to about 40%–50% of all trades, remains at that elevated level for an extended period of time, and gradually declines to pre-default levels over the following weeks, consistent with the trading activity documented in Figure 1. Overall, Figure 4 documents a shift in the intermediation towards primary dealers when a bond defaults.

We next use the following Probit specification to test the hypothesis that post-default investors are more likely to sell their defaulted bond positions to primary dealers and this propensity depends on the bond's pre-default ownership structure:

$$\begin{aligned}\Pr(\mathit{PrimaryDealer}_{ij} \mid \mathit{Trade}^{CD}_{ij}) = \Phi(\alpha_0 + \alpha_1\, \mathit{PostDefault}_{ij} \times \mathrm{HHI}_j + \\ + \alpha_2\, \mathit{PostDefault}_{ij} + \alpha_3\, \mathrm{HHI}_j + \beta'\, X_{ij}),\end{aligned} \tag{1}$$

with the standard errors adjusted for heteroskedasticity and clustered by bond issue and time. The key variable of interest in the specification (1) is a dummy variable $\mathit{PostDefault}_{ij}$ equal to one if trade i takes place during the post-default period and zero otherwise. $\mathit{PrimaryDealer}_{ij}$ indicates whether the bond j in the client-to-dealer (CD) trade i, labeled as Trade^{CD}_{ij}, is sold to a primary dealer. We add the ownership concentration (Herfindahl–Hirschman index, HHI_j) of institutional investors including insurance companies, bond mutual funds, and pension funds in bond j prior to default, available via eMAXX data. It proxies for a supply shock, given that investment restrictions may force these investors to sell a bond once it defaults.[11] Therefore, a high ownership concentration of institutional investors in a bond is expected to dry up its market liquidity, and investors who want to sell need to find specialized dealers that still provide liquidity. To differentiate the effect of the default event in the propensity to trade with a primary dealer subject to liquidity dry-up, we interact

[11] Investment mandates, internal and external regulatory constraints restrict certain investors such as insurance companies, bond mutual funds, and pension funds in the composition of investment portfolios. Except for the spike in volume around the default date, defaulted debt securities may no longer trade in a liquid market. Thus, the sale decisions may not be rational from an unrestricted investor's perspective. Consistently, May (2010), Ellul, Jotikasthira, and Lundblad (2011), Bao, O'Hara, and Zhou (2018), and Reichenbacher and Schuster (2022) show that supply shocks can already be observed in rating downgrades.

$PostDefault_{ij}$ with HHI_j. We control for unobserved heterogeneity by including dummies for different default event types, $DefaultType_j$, as well as year fixed effects and trade and bond characteristics, X_{ij}.[12] The sample comprises 547,742 client-to-dealer transactions within the year before default and 30 days after that.[13]

Table 2 reports results from specification (1) without, column 1, and with, column 2, the interaction term of $PostDefault_{ij}$ with HHI_j. Results from column 1 indicate that primary dealers are *more* likely to intermediate bonds after they default. The regression coefficient on $PostDefault_{ij}$ equal to 0.16 is positive and statistically significant at 5%-level. The pre-default ownership concentration of institutional investors is neither economically nor statistically significant in this specification. Column 2 of Table 2 reports a positive and statistically significant at the 1%-level regression coefficient of 0.29 on the interaction term. It demonstrates that transactions in bonds with concentrated institutional ownership before default are more likely to be intermediated by primary dealers after default. In addition, the $PostDefault_{ij}$ remains positive and significant. Customer-to-dealer trading shifts to primary dealers once a bond defaults. This phenomenon becomes stronger if the bond is held by institutional investors before the default surprise.

Retail-size trades, defined as trades with less than $100,000 par value, are more likely to be intermediated by primary dealers both before and after default. The retail dummy indicator is highly statistically significant at 1% with a coefficient of 0.24 in both columns. The dummy indicator for large institutional-size trades, defined as trades above $1 million par value, is not significant. Thus, for large trades, there is no tendency to trade with primary or non-primary dealers. Bonds with longer maturity are more likely to be sold to primary dealers, and older bonds and bonds with smaller issue sizes are less likely to be sold to

[12] These characteristics are comparable to those used by Li and Schürhoff (2019) to predict investors' choice to sell to central dealers in the municipal bond market. However, as we examine the corporate bond market, certain bond characteristics differ from those available for the municipal bond market.

[13] The number of observations is lower than in Table 1, which contains 625,548 transactions over the same period, given that ownership data is missing for some bonds in the eMAXX database.

Table 2: **Trading with primary dealers before and after default.** Specification 1 is a Probit specification that estimates the probability of clients trading with primary dealers. A total of 547,742 (434,754 pre-default and 112,988 post-default) client-to-dealer trades are considered. The *PostDefault* dummy variable indicates whether a trade takes place after the default event. For comparison, specification 2 uses dealer centrality as the dependent variable in an otherwise similar OLS specification. The explanatory variables further include default event type, trade characteristics, bond characteristics, and year fixed effects. Non-binary explanatory variables are normalized with center 0 and standard deviation 1. Standard errors are adjusted for heteroskedasticity and clustered by issue and time. Significance is denoted *** (1%), ** (5%), and * (10%).

	$PrimaryDealer_{ij} \mid Trade^{CD}_{ij}$	
Specification	(1)	(2)
$PostDefault \times$ Pre-default HHI		0.29***
$PostDefault$	0.16**	0.13**
Pre-default HHI	0.06	−0.02
Retail	0.24***	0.24***
LargeInstitutional	−0.05	−0.04
Distressed exchange	−0.04	−0.08
Risk rating	0.10	0.06
Chapter 11	0.16	0.12
Chapter 7 liquidation	0.35	0.30
Maturity	16.53***	15.43***
Seasoning	−0.10***	−0.09***
Issue size	−0.22***	−0.19**
Rating	−0.18	−0.15
Junk-rated	−0.13	−0.20
Unrated	−0.01	−0.04
Enhanced	−0.02	−0.01
Callable	0.42***	0.39***
Sinking fund	0.56**	0.53*
Senior unsecured	0.18*	0.18*
Senior subordinate	0.26**	0.25**
Subordinate junior	−0.05	−0.09
Coupon	−0.02	−0.02
CDS availability	0.11	0.10
Covenants	−0.08	−0.10
# observations	547,742	547,742

primary dealers. For the defaulted bonds, our analysis confirms the hypothesis that default events trigger a change in investors' trading decisions. Given investors' need to sell recently defaulted bonds, investors are more likely to approach primary dealers once a bond default occurs. Results from column 2 demonstrate that primary dealers intermediate transactions in defaulted bonds when liquidity dries up due to the surprise element of default.

Overall, these results highlight the changing patterns in the intermediation of defaulted corporate bonds. Bonds in good standing are intermediated by all dealers. After the default, the non-primary dealers cut back their intermediation of defaulted bonds potentially due to risk, inventory costs, regulatory constraints, or a combination of all three. The primary dealers pick up the slack in intermediating defaulted bonds. These findings are consistent with theories of dealers' endogenous trading skills and expertise (Glode and Opp, 2019; Hugonnier, Lester, and Weill, 2019; Sambalaibat, 2022; Chaderina and Glode, 2023). Primary dealers gain expertise in intermediating defaulted bonds by handling a large share of the order flow in these bonds before their default.

After having established that the client-dealer network for a bond changes after a bond default, we now test how these changes in the dealer-client intermediation affect investors' recovery of default losses suffered.

2 Post-Default Recovery Rates and Primary Dealers

Having identified the shift in trading patterns around corporate bonds' default events in Section 1.3, we now examine whether the intermediation by primary dealers leads to larger post-default recoveries for defaulted bond investors. Existing studies estimate recovery rates, defined as the price obtained by investors who sell recently defaulted bonds, by focusing on three main economic drivers: firm-specific characteristics, instrument-specific characteristics, and macroeconomic conditions.[14] We show that recovery rates are determined by primary

[14] See, for example, Altman and Kishore (1996), Altman, Brady, Resti, and Sironi (2005), Acharya, Bharath, and Srinivasan (2007), Bruche and Gonzalez-Aguado (2010), and Nazemi and Fabozzi (2018). Few studies have considered observable market dynamics of defaulted debt securities when estimating recovery rates. Altman, Brady, Resti, and Sironi (2005) explain aggregate annual bond recovery rates as a function of aggregate supply and demand for defaulted debt securities by evaluating quoted bond prices. Jankowitsch, Nagler, and Subrahmanyam (2014) extend this market-based approach to recovery rate modeling by implementing bond liquidity proxies derived from trading volumes and prices available from TRACE.

dealers' expertise in addition to factors outside of the dealers' realm. Hence, recovery differs not only across bonds but also across dealers and investors in the same bond.

2.1 Measuring primary dealers' impact on recovery rates

The following model accounts for the fact that the primary dealer status is an endogenous choice and outcome of the investor-dealer matching process. Let $PrimaryDealer_{ij}$ indicate the investor's choice of the dealer with $PrimaryDealer_{ij} = 1$ for a primary dealer and $PrimaryDealer_{ij} = 0$ for a non-primary dealer. To capture the impact of dealer intermediation on bond recovery, consider the recovery rate RR^0_{ij} (RR^1_{ij}) for transaction i in bond j that can be achieved by trading through a non-primary (primary) dealer. The difference in potential recovery rates RR_{ij} between primary and non-primary dealers captures the primary dealer's skill and expertise in intermediating the bond:

$$RR^1_{ij} = RR^0_{ij} + \delta\, PrimaryDealer_{ij}. \tag{2}$$

An important empirical question is whether primary dealer expertise $\delta \equiv RR^1 - RR^0$, which can also be interpreted as the causal effect of trading with primary dealers and which is separate from the selection effect of trade choice, is value improving, $\delta \geq 0$, or value-destroying, $\delta < 0$. Primary dealers could add value in the post-default process via their prior experience in intermediating distressed bonds. For instance, allocating defaulted bonds to more concentrated bondholders improves their coordination leading to increased bargaining power in post-default negotiations (Lewis, 2016).

To estimate the primary dealer expertise δ in the data, we specify potential recoveries as $RR^d_{ij} = \mu^d(X_{ij}) + \epsilon^d_{ij}$, $d = 0, 1$, with observed determinants X_{ij} and unobserved determinants

ϵ_{ij}^d. For clarity, we assume linearity of the expected recovery term $\mu^d(X_{ij})$:

$$RR_{ij}^d = \alpha + \delta\, PrimaryDealer_{ij} + \beta' X_{ij} + \epsilon_{ij}^d, \quad d = 0, 1. \tag{3}$$

Observed recoveries in our sample can be decomposed as

$$RR_{ij} = (1 - PrimaryDealer_{ij}) \times RR_{ij}^0 + PrimaryDealer_{ij} \times RR_{ij}^1. \tag{4}$$

How to estimate δ (and the recovery rate determinants β) depends on the assumptions we make on how investors match with dealers after the bond's default. We perform the analysis both at the trade and bond levels.

2.2 Trade-specific recovery rates

We start with the most granular data by estimating recovery rates at the trade level for investors selling to primary dealers in order to better understand the marginal effect of primary dealer intermediation on recoveries and the heterogeneity therein across investors. We define the trade-level recovery rate for transaction i in bond j, RR_{ij}, as a ratio of the transaction price $price_{ij}$ to the bond's par value, par_j:

$$RR_{ij} = \frac{price_{ij}}{par_j}. \tag{5}$$

We utilize transaction prices reported to TRACE during the 30-day post-default period, which is the commonly used market convention for defining recovery rates. For bondholders who sell promptly after default or mark their investments to market, the price at default represents actual recovery on investment (Acharya, Bharath, and Srinivasan, 2007). The trade-specific rates in our sample are therefore representative of investor-specific recovery.

We set up the following baseline regression specification to model trade-level recovery rates employing the explanatory variables established in the recovery rate literature and adding the primary dealer indicator as a determinant:

$$RR_{ij} = \alpha + \delta \, PrimaryDealer_{ij} + \beta' \, X_{ij} + \epsilon_{ij}. \tag{6}$$

The controls X_{ij} in (6) include fixed effects of the different default event types, seniority, year, industry, and industry distress fixed effects as well as bond, liquidity, macroeconomic, and company features. We cluster standard errors by bond issue and time. We also add dealer fixed effects in a "saturated" specification to focus on the default-episode specific role of $PrimaryDealer_{ij}$. A total of 108,536 post-default client-to-dealer trades are included in the recovery rate specification.

Table 3 reports the regression results for (6) estimated from trade-level recovery rates. We focus on the effect of transacting with a primary dealer, $PrimaryDealer_{ij}$, on the trade-specific recovery rate. The standard OLS specification (specification 1) yields an extra recovery of \$4.52 per \$100 invested, both statistically at the 1%-level and economically significant. Given that the mean bond-level recovery rate in our sample is \$38.8 per \$100 invested, this implies a more than 10% premium obtained by investors who sell via primary dealers.

Specification 2 adds dealer fixed effects to specification 1. It yields a consistent sign and significance of the extra recovery from trading with a primary dealer as specification 1, although at a smaller magnitude of \$2.03 per \$100 invested, thus indicating that some fraction of the pricing benefit captured by the primary dealer is likely absorbed by other dealer-specific characteristics.

IV approach. A potential concern with explaining transaction-level recovery rates (4) is that common shocks can affect both a bond's recovery after the default and primary dealers' incentives to intermediate this bond. For instance, primary dealers may select bonds with higher anticipated recovery rates after the default without making any contribution to the price recovery themselves. This is because an important consideration for recovery and debt renegotiation post-default is the extent to which creditors can recoup funds by being informed and aligned. Along these lines, post-default ownership concentration can affect recovery on defaulted bonds in several ways. When the ownership of a bond is concentrated, the holders are more likely to have access to information about the bond's issuer. They also have greater bargaining power with the issuer of the bond, since they can threaten to sell their bonds which drives down the price even further and forces the issuer to make concessions. When ownership of a bond is concentrated in a small number of holders, it is also easier for them to agree on a restructuring plan in the event of a default. Finally, there is less fragmentation of interests among the holders which can make it easier for the holders to act collectively in their own best interests. In summary, because post-default concentrated ownership can lead to reduced information asymmetry, improved incentives to monitor, enhanced bargaining power, facilitated restructuring, and reduced fragmentation of interests, it is associated with improved post-default recovery rates.

To account for the endogenous investor-dealer matching after the bond's default, we consider the investor's net benefit $I_{ij} = \mu(Z_{ij}) - U_{ij}$ of trading with a primary dealer which depends on observed determinants $Z_{ij} = (W_j, X_{ij})$ and an unobserved component U_{ij}, where $\mu(\cdot)$ is an unspecified function and U_{ij} is a continuous random variable with a strictly increasing distribution function F_U. The determinants Z_{ij} include proxies for the dealer's experience and connections, expected trade delays, and other intermediation services provided by the dealer. W_j is an instrument affecting the investors' choice and satisfying the exclusion restriction.

Based on information about bond ownership from the eMAXX database, we use as the first-stage instrument W_j the pre-default ownership concentration (Herfindahl–Hirschman index, HHI_j) of institutional investors including insurance companies, bond mutual funds, and pension funds in bond j prior to default, similar to (1). It captures that investors who want to sell need to find specialized dealers that still provide liquidity. The identifying assumption here is that the pre-default ownership concentration among institutional investors affects bond-level recoveries through investors' trade-level decisions of routing their orders to a primary dealer, but HHI_j does not directly affect recovery. Investors' dealer choice can be expressed as

$$PrimaryDealer_{ij} = 1 \Leftrightarrow \mu(Z_{ij}) > U_{ij} \Leftrightarrow F_U(\mu(Z_{ij})) > F_U(U_{ij}) \Leftrightarrow P(Z_{ij}) > U_{ij}.$$

Written in this way, $P(Z_{ij})$ denotes the propensity score that captures the probability of selecting a primary dealer while U is a uniformly distributed random variable between 0 and 1 representing the propensity to trade with a non-primary dealer. Under linearity, the propensity to trade with a primary dealer equals: $\Pr(PrimaryDealer_{ij}|\mathrm{HHI}_j, X_{ij}) = P(\alpha + \theta\,\mathrm{HHI}_j + \gamma' X_{ij})$, where θ is the effect on the primary dealer choice of factors unrelated to recovery rates.

We can use a standard IV approach to account for endogeneity in specification (6). To implement the primary dealer choice in our data, we estimate in the first stage the following Probit model: $\Pr(PrimaryDealer_{ij}|\mathrm{HHI}_j, X_{ij}) = \Phi(\alpha + \theta\,\mathrm{HHI}_j + \gamma' X_{ij})$. In the second stage, we use in specification (6) the predicted value $\widehat{PrimaryDealer}_{ij} = \widehat{\Pr}(PrimaryDealer_{ij})$ from the first stage specification instead of indicator $PrimaryDealer_{ij}$.

The left column in Table 3 reports the results for the first stage. The instrument is significant in this specification, supporting the instrument's validity. The positive sign suggests that when a bond's ownership structure is more concentrated among insurance companies,

Table 3: **Trade-based recovery rates.** The left column is the Probit specification that estimates the probability of clients trading with primary dealers when selling recently defaulted bonds in order to create the instrumental *PrimaryDealer* variable. The binary *PrimaryDealer* variable indicates whether the bond is sold to a primary dealer. The recovery rate *RecoveryRate* is the dependent variable in specifications 1–5. Specification 2 controls for dealer-specific effects. Specifications 3–5 control for potential endogeneity, selection bias, and essential heterogeneity. A total of 108,536 post-default client-to-dealer trades are considered for recovery rate estimation. Non-binary explanatory variables are normalized with center 0 and standard deviation 1. Standard errors are adjusted for heteroskedasticity and clustered by issue and time. Significance is denoted *** (1%), ** (5%), and * (10%).

	$PrimaryDealer_{ij}$	Trade-level recovery rate RR_{ij}				
		(1)	(2)	(3)	(4)	(5)
Specification	1st stage	OLS	Saturated	IV	Heckman	MEH
$PrimaryDealer$ ($\times p$ in (5))		4.52***	2.03***	6.79***	4.24***	7.72***
Lambda					−7.52	
p						−21.23*
p^2						22.03***
Pre-default HHI	0.78***					
LargeInstitutional	0.16	−0.23	−1.22**	−0.42	−0.37	−0.21
Retail	0.51***	−0.24	0.25	−0.29	−0.61	0.56
Distressed exchange	1.02***	12.36***	11.63**	11.61**	11.53**	14.36***
Risk rating	0.96***	14.32***	14.50***	13.59***	13.58***	15.60***
Chapter 11	0.71***	−2.05	−2.31	−3.00	−2.65	−1.03
Chapter 7 liquidation	1.29	0.90	0.00	−0.10	−0.11	2.58
Seniority FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry distress FE	Yes	Yes	Yes	Yes	Yes	Yes
Bond features	Yes	Yes	Yes	Yes	Yes	Yes
Liquidity features	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic features	Yes	Yes	Yes	Yes	Yes	Yes
Company features	Yes	Yes	Yes	Yes	Yes	Yes
Dealer FE	No	No	Yes	No	No	No
R^2		0.5959	0.6185	0.5942	0.5961	0.6009
# observations	108,536	108,536	108,536	108,536	108,536	108,536

pension funds, and bond mutual funds, we observe a higher propensity of investors to sell to primary dealers after a default event. This is expected if institutional investors cause a supply shock in response to default, increasing the need for specialized dealers that provide sales channels to potential investors.

Table 3 reports the IV regression results estimated from trade-level recovery rates in column (3). We again focus on the effect of transacting with a primary dealer, $PrimaryDealer_{ij}$, on the transaction-specific recovery rate. The IV specification 3 produces an extra recovery of \$6.79 per \$100 par value from transacting with primary dealers, both statistically at the 1%-level and economically significant and larger than the OLS estimates.

An alternative way to adjust for biased estimates stemming from investors' dealer selection is to employ a Heckman (1979) correction approach. We use it in specification 4 of Table 3 with the same instrument as in specification 3. In this specification, we control for selection bias by adding to specification 1 the inverse Mills ratio, Lambda, as an additional explanatory variable as per Heckman (1979). Again, the *PrimaryDealer* variables increases recoveries by \$4.24 per \$100 par value, both statistically at the 1%-level and economically significant and close to the OLS estimate.

Accounting for heterogeneity in the dealers' impact on recoveries. Another concern that could affect our estimates is that the selection of a primary dealer may be based on unobserved benefits. This is the case if investors that choose primary dealers have different benefits than others, which is likely the case in our setting for forced sellers. Unlike assuming homogeneity where all investors are treated as identical or similar in all relevant aspects, models of essential heterogeneity recognize and incorporate the idea that investors and bonds possess unique characteristics that are essential to understanding their behavior and outcomes (Heckman and Vytlacil, 2007; Brinch, Mogstad, and Wiswall, 2017).

To exploit the heterogeneity in recovery rates across investors and bonds, we introduce a control function for the predicted primary vs. non-primary dealer choice. We denote by $K^d(p)$ the selection corrections for the expected recovery surprises for primary and non-primary dealers, respectively,: $K^1(p) = \mathbb{E}[\epsilon^1|U \leq p]$, $K^0(p) = -\frac{p}{1-p}\mathbb{E}[\epsilon^0|U \leq p]$, and

$$K(p) = pK^1(p) + (1-p)K^0(p). \tag{7}$$

$K^d(p)$ are unspecified functions of the propensity score p with two regularity conditions: $\lim_{p\to 0} K^1(p) = 0$, $\lim_{p\to 1} K^0(p) = 0$.[15]

We can estimate the expertise δ and determinants β of recovery rates in the sample of trades with primary and non-primary dealers by recognizing that

$$RR^d_{ij} = \alpha + \delta\, PrimaryDealer_{ij} + K^d(p_{ij}) + \beta' X_{ij} + \varepsilon^d_{ij}, d = 0, 1, \tag{8}$$

with mean-zero errors ε^d_{ij}. Observed recoveries in our sample can now be decomposed and jointly estimated from the following model of essential heterogeneity (MEH):[16]

$$RR_{ij} = \alpha + \delta\, PrimaryDealer_{ij} \times p_{ij} + \lambda\, K(p_{ij}) + \beta' X_{ij} + \varepsilon_{ij}, \tag{9}$$

with mean-zero error ε_{ij} and $K(p_{ij})$ is the Mills term defined in (7) and treated as an unspecified function of the propensity of trading with a primary dealer during a bond default. $K(p) \le 0$ satisfies $\lim_{p\to 0} K(p) = \lim_{p\to 1} K(p) = 0$ and can be semi-parametrically estimated by polynomials of order l. In our implementation, we vary l and report results for $l = 2$.

The last column of Table 3 reports results from specification (9). The propensity to trade with a primary dealer, p_{ij}, is estimated from the Probit model in Section 2.2. The negative and statistically significant coefficient on p_{ij} and positive and statistically significant coefficient on p^2_{ij} indicate a strong essential heterogeneity in the propensity to transact with primary dealers. Consistent with the prior specifications, we find that the regression coefficient on the interaction term $PrimaryDealer_{ij} \times p_{ij}$ is positive at \$7.72 per \$100 par value and statistically significant at the 1%-level. Thus, investors decide to sell defaulted bonds to primary dealers while having at least partial knowledge of the idiosyncratic recovery

[15] Under normality assumptions, $K^d(p)$ is proportional to the inverse Mills ratio.

[16] The term "essential heterogeneity" was introduced by Heckman, Smith, and Clements (1997) to describe situations where the effects of treatment vary across individuals and cannot be fully explained by observable characteristics since there exist unobservable factors that influence an individual's response to treatment.

outcomes of such dealer selection.[17]

Overall, the results from specifications 3–5 imply that clients expect to recover between $4 and $7 more per each $100 invested on each transaction when transacting with primary dealers instead of other dealers, and about $2 when primary dealers' other unobserved characteristics are accounted for via dealer fixed effects. The significant positive coefficients δ on primary dealers in all specifications show that trading with primary dealers positively impacts trade-level recovery rates. These results provide support to the hypothesis based on the theoretical work of Glode and Opp (2019), Hugonnier, Lester, and Weill (2019), Sambalaibat (2022), and Chaderina and Glode (2023) that primary dealers possess special expertise and skills in intermediating defaulted bonds.

Robustness. All results reported in Table 3 are robust to including and excluding controls for dealer centrality, dealer size, and dealer inventory, robust to replacing default type fixed effects with firm-level default event fixed effects, and robust to a more stringent client-centric primary dealer definition that considers as primary dealers those dealers who intermediate the largest number of client-to-dealer trades rather than considering all trades prior to default.

In Appendix B, we explore the robustness of the results using two alternative instruments. Tables B.1 and B.2 summarize the results using the alternative instruments. In Table B.1, we replace HHI with the pre-default number of different investor types, which we obtain from eMAXX. Table B.2 employs the total number of individual investors rather than the number of investor types. Both tables yield similar results and confirm our findings on the trade-level recovery rate.

[17] If we consider third or fourth-order polynomials, signs and significance of the interaction $PrimaryDealer_{ij} \times p_{ij}$ remains stable, and the other coefficient estimates do not change materially.

Table 4: **Summary statistics for per-bond bond-level recovery rates.** The recovery rate is calculated as the average trading price in cents per 100 cents in par value, of transactions on the default day and during the 30-day period thereafter.

	Mean recovery rate RR_j in defaulted bond j (% of par)								
	Mean	*SD*	*Min*	*q25*	*q50*	*q75*	*Max*	*N*	*% total*
All defaulted bonds	38.8	28.8	0.0	13.8	34.2	57.2	119.8	2,636	100.0%
Distressed exchange	59.2	29.8	0.4	30.3	59.6	84.8	113.7	197	7.5%
Default risk rating	57.5	27.4	5.7	34.2	58.7	80.5	119.8	306	11.6%
Chapter 11	37.5	28.0	0.0	12.3	36.7	53.6	119.6	1,520	57.7%
Default rating	26.3	20.7	0.0	13.2	15.9	35.1	106.6	542	20.6%
Chapter 7 liquidation	26.3	34.0	0.0	0.3	11.6	42.5	99.9	71	2.7%

2.3 Bond-level recovery rates

The impact of dealer expertise on the firm and creditors ex-ante can be measured by aggregating trade-level recovery rates at the bond level. The mean recovery rate in bond j, similar to the one used in Jankowitsch, Nagler, and Subrahmanyam (2014), equals:

$$RR_j = \frac{1}{T+1} \sum_{s=t}^{t+T} \left(\frac{1}{|K_{js}|} \sum_{i \in K_{js}} RR_{ij} \right), \tag{10}$$

where t is the bond's default date, T is the horizon, and K_{js} is the number of reported bond transactions in bond j on day s. To calculate RR_j we consider transactions reported to TRACE between the default date t and 30 days thereafter.

Table 4 reports summary statistics for bond-level recovery rates defined in (10) and split by the event type. The table shows a wide variation in recovery rates. The mean recovery rate in our sample is 38.8% with a standard deviation of 28.8% and a spike at 10-20%. The statistics are in line with the 40% recovery rate that has historically been used as a fixed recovery estimate, as noted by Altman and Kishore (1996). Consistent with the literature, distressed exchange events exhibit the highest recovery rates (Franks and Torous, 1994; Varma and Cantor, 2005; Mora, 2015). Default risk rating downgrades (e.g.

S&P's C rating) yield the second-highest recoveries whereas actual default ratings (e.g., S&P's D rating) and Chapter 7 liquidations show the worst recovery rates. Default risk rating downgrades may occur well ahead of a formal default event and creditors may then be able to impose more timely measures to preserve their investments, e.g., selling their bond holdings before the firm's situation worsens, or influencing the debtor. The wide variation in recovery rates that we observe occurs across bonds and time. Over time, the post-global financial crisis years 2009 and 2014 and the credit market stress year 2016 yielded the lowest recoveries. Across industries, bonds from utilities (electricity and gas) recover the most; financial services and savings/loan providers have the worst recovery rates (Jankowitsch, Nagler, and Subrahmanyam, 2014; Mora, 2015).

To check the impact of the primary dealer intermediating defaulted bonds on bond-level recovery, we record whether an intermediating dealer is a primary dealer in a client-to-dealer trade and then average across trades. For a given bond, we define the percentage share of trades that are performed by the primary dealer as:

$$PrimaryDealer_j \equiv \frac{1}{K_j} \sum_{i=1}^{K_j} PrimaryDealer_{ij}, \tag{11}$$

where K_j is the number of client-to-dealer trades in bond j.

Bond-level shift-share instrument. To control for the endogeneity of (11), we construct a Bartik (1991) type shift-share instrument at the bond level. In the spirit of Bartik (1991), we instrument the percentage share of primary dealers $PrimaryDealer_j$ participating in the trades of bond j through the expected primary dealer share by first estimating trading with the primary dealer for each transaction using the first stage IV Probit specification in Section 2.2. We then aggregate the predicted trade-level primary dealer participation, $\widehat{\Pr}(PrimaryDealer_{ij})$, to an expected percentage share of primary dealer trading for each

Table 5: **Bond-level recovery rates.** The *PrimaryDealer* variable represents the share of client-to-dealer transactions where a given bond is sold to a primary dealer. The mean recovery rate RR_j is the dependent variable in specifications 1 - 4. A total of 2,093 and 1,275 defaulted bonds are considered in specifications 1/3, and 2/4, respectively. Explanatory variables, other than the *PrimaryDealer* and binary variables, are normalized with center 0 and standard deviation 1. Standard errors are adjusted for heteroskedasticity and clustered by firm and time. Significance is denoted *** (1%), ** (5%), and * (10%).

	Mean recovery rate RR_j			
	(1)	(2)	(3)	(4)
Specification	OLS	Bartik-IV	OLS	Bartik-IV
PrimaryDealer	6.79**	4.03*	6.08**	4.67*
Central dealer			−3.04***	−3.94***
Dealer size			1.99*	2.74***
Dealer inventory			−1.12	−2.14***
Trade size	−7.58**	−9.53***	−7.46**	−9.24***
Distressed exchange	18.90***	17.95***	18.91***	17.88**
Risk rating	16.01***	14.98***	16.15***	14.78***
Chapter 11	0.28	−0.64	−0.07	−0.87
Chapter 7 liquidation	0.64	5.34	0.44	5.20
Bond features	Yes	Yes	Yes	Yes
Seniority FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Industry distress FE	Yes	Yes	Yes	Yes
Liquidity features	Yes	Yes	Yes	Yes
Macroeconomic features	Yes	Yes	Yes	Yes
Company features	Yes	Yes	Yes	Yes
R^2	0.6303	0.6273	0.6312	0.6297
# observations	2,093	1,275	2,093	1,275

defaulted bond:

$$\widehat{PrimaryDealer}_j = \frac{1}{K_j} \sum_{i=1}^{K_j} \widehat{\Pr}(PrimaryDealer_{ij}). \tag{12}$$

We set up a specification similar to (6) to model bond-level recovery rates using the same explanatory variables if possible and adding the percentage share of primary dealer intermediation as an additional explanatory variable[18]

$$RR_j = \alpha + \delta\, \widehat{PrimaryDealer}_j + \beta'\, X_j + \epsilon_j, \tag{13}$$

with standard errors adjusted for heteroskedasticity and clustered by issue and time.

Results. Table 5 reports results for the impact of the intermediation by primary dealers on bond-level recovery rates. We first discuss OLS estimates for δ. In specification 1, we use the share of primary dealer participation across all post-default trades. Specification 3 is identical to specification 1 except we control for dealer characteristics such as central dealer as a binary indicator denoting whether a dealer is located in the network's core, dealer size, and inventory. The estimate of δ is economically large and statistically significant at 5%-level. OLS regression specifications (1)/(3) suggest that recovery rates for a given bond are \$6.79/\$6.08 per \$100 invested higher when transacting with primary dealers instead of non-primary dealers.

Specifications 2 and 4 are identical to specifications 1 and 3, respectively, except that we use the instrumented share of the primary dealer participation across all post-default trades in bond j, $\widehat{PrimaryDealer}_j$. The number of observations is lower in columns 2 and 4 because the eMAXX data is missing in some cases. The IV estimates are smaller than the OLS estimate, at values of \$4.03/\$4.67 per \$100 par value. The estimates are also similar to the estimate of the trade-specific recovery rate from column 1 of Table 3. Since the coefficient on the primary dealer indicator is positive and significant in all specifications, there is a positive relationship between trading with primary dealers and recovery rates at the bond level which is robust when controlling for mean dealer size, inventory, and centrality.

[18] These variables are widely used in the existing literature see, for example, Acharya, Bharath, and Srinivasan (2007), Jankowitsch, Nagler, and Subrahmanyam (2014), Mora (2015), and Nazemi and Fabozzi (2018)).

The regression coefficient on the central dealer dummy is equal to $-3.04/-3.94$ in columns 3/4, and it is both economically and statistically significant. Its negative sign also provides support to a hypothesis that central dealers play a different role than primary dealers when intermediating defaulted corporate bonds. This could be the "need for speed" by institutions willing to trade the faster execution for inferior prices. Specifications 3 and 4 also show that trading with larger dealers and dealers with more empty inventories improves the bond-level recovery. The other regression coefficient estimates suggest that recovery rates decline with the average trade size and that recovery rates are higher in distressed exchanges and risk-rating cases.

In summary, we find that trading with primary dealers yields trade-level price premia of \$2.03 to \$7.72 per \$100 invested and the bond-level premia of \$4.03 to \$6.79 per \$100 invested. A natural question is how primary dealers generate large recovery gains for investors. Next, we investigate the channels through which primary dealers increase recovery rates.

3 Role of Primary Dealers in Trading Defaulted Bonds

The literature offers several potential explanations for why primary dealers who are more familiar with the defaulted bond provide better recoveries than other dealers. One explanation is that, consistent with the model of Glode and Opp (2019), primary dealers possess superior expertise in intermediating the defaulted bond. Trading with a primary dealer may then result in better allocation efficiency leading to better recovery rates. Asymmetric information about the residual value of the bondholders who are subordinated claim holders rises after the default. Glode and Opp (2016) show that longer intermediation chains weaken traders' incentives to screen counterparties thus reducing the adverse selection and increasing trade efficiency. An alternative explanation of our findings is that primary dealers switch to riskless principal trades after the default and are capable of brokering trades at lower cost and, hence, better prices (Bao, O'Hara, and Zhou, 2018; Li and Schürhoff, 2019; Goldberg and Nozawa, 2021). Yet another explanation is that primary dealers may have lower inventory costs and can pass some savings to buyers as price improvements (Bessembinder, Jacobsen, Maxwell, and Venkataraman, 2018).

To shed light on these channels, we investigate the intermediation chain lengths, dealers' role as brokers as opposed to principal traders, whether dealers are more likely to prearrange trades or place defaulted bonds in their inventories, and whether the extensive margins of intra-day trading, i.e., the probabilities of matching with the counterparty within a day, are lower for defaulted bonds than for regular bonds. In the final section, we investigate post-default price efficiency.

3.1 Intermediation chains in defaulted bonds

Here we examine whether intermediation chains change for bonds affected by default. Specifically, we are interested in how dealers match sellers and buyers of recently defaulted bonds. We analyze intra-day round-trip intermediation chain length to infer predictions on primary and non-primary dealers' ability to successfully and timely match the supply and demand in defaulted bonds.

To study the length of intermediation chains, we focus our analysis on a sub-sample of successful *intra-day* round trips.[19] Dealers may either complete the bond intermediation chain by selling to a client, or dealers may sell to another dealer, who then locates the next buyer. Ultimately, bond intermediation is completed through a chain of trades starting with a client-to-dealer trade and ending with a dealer-to-client trade, hence called a round-trip.[20]

[19] We consider intra-day round trips instead of round trips over several days for two reasons. First, only intra-day round trips can be distinctively allocated to either the pre- or the post-default period, as they do not overlap both periods. Second, the economics behind intra-day observations are less likely to be affected by interfering market dynamics or news events related to the defaulted bond that may alter the bond's trading characteristics during the intermediation process, as only a short time frame from the start of the intermediation to its completion is considered.

[20] We allow for trade splits to offset a dealer's position in a dealer-to-client sale.

In between, there may occur one or several consecutive dealer-to-dealer trades. We denote a complete round-trip with N dealers between the seller-client and the buyer-client as a *C(N)DC* intermediation chain. The head dealer within the chain either sells immediately to the next client (*CDC* round-trip), to the next dealer (*CDD* trade chain), or keeps the bond in inventory until the next buyer is located.

We estimate the determinants of the length of intra-day completed *C(N)DC* intermediation chains before and after default events using the following specification:

$$log(N_{ij}) \mid RoundTrip_{ij}^{C(N)DC} = \alpha_0 + \alpha_1\, PostDefault_{ij} \times PrimaryDealer_{ij} + \\ + \alpha_2\, PostDefault_{ij} + \alpha_3\, PrimaryDealer_{ij} + \beta'\, X_{ij} + \epsilon_{ij}, \quad (14)$$

with the standard errors adjusted for heteroskedasticity and clustered by bond issue and time. The sample consists of a total of 143,787 (124,438 pre-default and 19,349 post-default) intra-day *C(N)DC* round-trips. In specification (14), N_{ij} is the number of dealers within an intra-day completed *C(N)DC* intermediation chain i in bond j, denoted $RoundTrip_{ij}^{C(N)DC}$, and $PrimaryDealer_{ij}$ indicates whether the head dealer that offsets the initial client-to-dealer trade and initiates a successful intra-day round-trip is the primary dealer in that bond. Controls X_{ij} are the same as used in specification (1), but we add dealer characteristics such as size, centrality, inventory, and a dummy for a dealer acting as a broker. To control for unobserved dealer-specific characteristics, we add a saturated specification with dealer fixed effects in column (5).

Table 6, reports our results for specification (14) with, column 1, and without, columns 2–5, bond dummies. Column 1 shows that intermediation chains are 7% shorter for primary dealers (the regression coefficient is equal to -0.07 and statistically significant at the 1%-level), 12% longer for retail-size trades (the regression coefficient is equal to 0.12 and statistically significant at the 1%-level), and 22% shorter for large institution-size trades (the

Table 6: **Length of intra-day *C(N)DC* round-trip chains before and after default.** The table provides results of OLS regression that estimates the length of intra-day *C(N)DC* round-trip chains, under the condition that the initial client-to-dealer trade results in a complete intra-day *C(N)DC* round-trip. The dependent variable is the logarithm of the number of dealers within the intermediation chain between two clients. A total of 143,787 (124,438 pre-default and 19,349 post-default) intra-day *C(N)DC* round-trips are considered. The *PostDefault* dummy variable indicates whether a trade takes place after the default event. *PrimaryDealer* indicates whether the bond is sold to the primary dealer. The explanatory variables further include default event type, dealer characteristics, trade characteristics, bond characteristics, and year fixed effects. Non-binary explanatory variables are normalized with center 0 and standard deviation 1. Standard errors are adjusted for heteroskedasticity and clustered by issue and time. Significance is denoted *** (1%), ** (5%), and * (10%).

	$IntermediationChainLength_{ij}$				
Specification	(1)	(2)	(3)	(4)	(5)
$PostDefault \times PrimaryDealer$				0.13***	0.11***
$PostDefault$	−0.02*	0.01	0.00	−0.01	0.00
$PrimaryDealer$	−0.07***	−0.14***	−0.15***	−0.16***	−0.08***
Distressed exchange		−0.04*	−0.05**	−0.05**	−0.02
Risk rating		−0.08***	−0.08***	−0.08***	−0.05***
Chapter 11		−0.01	−0.02	−0.02	0.00
Chapter 7 liquidation		−0.13***	−0.10**	−0.10**	−0.10**
Dealer size			0.10***	0.10***	0.08***
Dealer centrality			−0.14***	−0.14***	−0.01
Broker role			−0.08***	−0.08***	−0.11***
Dealer inventory			0.01***	0.01***	0.01***
Retail	0.12***	0.20***	0.16***	0.16***	0.04***
LargeInstitutional	−0.22***	−0.28***	−0.28***	−0.28***	−0.19***
Maturity		−0.02***	−0.02***	−0.02***	−0.02***
Seasoning		0.01	0.01	0.01	0.01
Issue size		−0.01	−0.01	−0.01	0.00
Rating		−0.05***	−0.04***	−0.04***	−0.04***
Junk rated		0.13***	0.13***	0.13***	0.14***
Unrated		−0.07**	−0.04	−0.04	0.00
Enhanced		0.00	0.00	0.00	0.02*
Callable		−0.05***	−0.04***	−0.04***	−0.03***
Sinking fund		−0.07	−0.07	−0.07	−0.05
Senior unsecured		0.04**	0.03**	0.03**	0.02**
Senior subordinate		0.01	0.02	0.02	0.01
Subordinate junior		0.03	0.04	0.04	0.06**
Coupon		0.02***	0.02***	0.01***	0.01***
CDS availability		0.03***	0.02**	0.02**	0.01
Covenants		0.00	0.00	0.00	0.02*
Bond FE	Yes	No	No	No	No
Dealer FE	No	No	No	No	Yes
# observations	143,787	143,787	143,787	143,787	143,787

regression coefficient is equal to −0.22 and statistically significant at the 1%-level). While the regression coefficient on the post-default dummy is negative and equal to −0.02, it is not economically significant and statistically significant only at the 10%-level.

When we use bond characteristics instead of bond dummies, column 2 of Table 6, and then add dealer size, centrality, inventory, and the broker role dummy, column 3 of Table 6, the regression coefficient on the post-default dummy loses its statistical and economic significance. Columns 2/3 show that intermediation chains are 14%/15% shorter for primary dealers, 20%/16% longer for retail-size trades, and 28% shorter for large institution-size trades. The length of intermediation chains increases with the dealer size and inventory, and they are longer for coupon-paying and riskier bonds, i.e., for high-yield bonds, senior unsecured and junior subordinate bonds issues, and bonds with CDS contracts. The length of intermediation chains declines with dealer centrality (except for specification 5), and it is shorter in dealer-brokered trades, for bonds with a longer maturity, callable, and lower-rated bonds, and bonds traded on the rating downgrade default events. Finally, intermediation chains are shorter for bonds of firms in Chapter 7 liquidations.

We add the interaction term between the primary dealer and post-default dummies to the specification in column 3 of Table 6 and report the results in column 4 without, and in column 5 with dealer fixed effects. The regression coefficient on the interaction term is equal to 0.13 and 0.11, respectively, and both are statistically significant at the 1%-level. This implies that intermediation chains for primary dealers are 13%/11% longer post-default than for other dealers. Thus, primary dealers' intra-day matching capability is more affected by default events. By contrast and in line with Hollifield, Neklyudov, and Spatt (2017), intermediation chains initiated by central dealers are generally shorter than those initiated by non-central dealers, and similarly, dealers that act as agencies without taking inventory risk initiate shorter intermediation chains.

3.2 Broker vs. dealer role

During normal times, dealers absorb excess supply in corporate bonds through their balance sheets (Goldberg and Nozawa, 2021). We examine primary dealers' tendency to take bonds into inventory as opposed to prearranging trades in defaulted bonds in the role of a broker. We consider trades denoted as agency trades in TRACE and principal trades that are offset within one minute as agency trades.[21]

We estimate the effect of default on dealers' role as brokers versus principals in a Probit specification that controls for a variety of alternative factors, employing 625,548 client-to-dealer trades during the year before a bond's default event until 30 days thereafter:

$$\begin{aligned}\Pr(\mathit{BrokerRole}_{ij} \mid \mathit{Trade}_{ij}^{CD}) = \Phi(&\alpha_0 + \alpha_1\, \mathit{PostDefault}_{ij} \times \mathit{PrimaryDealer}_{ij} + \\ &+ \alpha_2\, \mathit{PostDefault}_{ij} + \alpha_3\, \mathit{PrimaryDealer}_{ij} + \beta'\, X_{ij}), \quad (15)\end{aligned}$$

with standard errors adjusted for heteroskedasticity and clustered by bond issue and time. The dependent variable indicates whether the dealer acts as a broker ($\mathit{BrokerRole}_{ij} = 1$) or principal ($\mathit{BrokerRole}_{ij} = 0$). Controls X_{ij} include trade and bond characteristics, and year fixed effects.

Table 7 provides results for the Probit estimates for the dealer's role. In specifications 1–3, we find that dealers are significantly less likely to act as brokers once a bond defaults. This highly significant effect suggests that dealers provide immediacy to sellers of recently defaulted bonds who must sell defaulted bonds quickly. Dealers take recently defaulted bonds and the associated risks on their own balance sheets rather than searching for a willing buyer first. We further find a strong negative effect of primary dealers in specifications 1–3 where we do not add primary dealer interactions which demonstrates that primary dealers more readily

[21] Our definition of agency trades follows the standard convention in the literature and is in line with Bessembinder, Jacobsen, Maxwell, and Venkataraman (2018), Bao, O'Hara, and Zhou (2018), and Li and Schürhoff (2019). In Appendix A, we provide more information on the prevalence of agency trades.

Table 7: **Broker vs. dealer role before and after default.** Probit regression for the probability of dealers to trade as brokers when buying bonds from clients. The dependent variable indicates 1 when the dealer takes the role of a broker (agency) and 0 otherwise (principal). A total of 625,548 (494,050 pre-default and 131,498 post-default) client-to-dealer trades are considered. The *PostDefault* dummy variable indicates whether a trade takes place after the default event. *PrimaryDealer* indicates whether the bond is sold to the primary dealer. The explanatory variables further include dealer characteristics, default event type, trade characteristics, bond characteristics, and year fixed effects. Non-binary explanatory variables are normalized with center 0 and standard deviation 1. Standard errors are adjusted for heteroskedasticity and clustered by issue and time. Significance is denoted *** (1%), ** (5%), and * (10%).

	$\Pr(BrokerRole_{ij})$				
Specification	(1)	(2)	(3)	(4)	(5)
$PostDefault \times PrimaryDealer$				−1.09***	−1.13***
$PostDefault$	−0.11***	−0.18***	−0.21***	−0.03	−0.02
$PrimaryDealer$	−0.25***	−0.27***	−0.23**	−0.01	0.31***
Distressed exchange		−0.10*	−0.13**	−0.09	−0.08
Risk rating		−0.08	−0.10*	−0.07	−0.05
Chapter 11		−0.11**	−0.16***	−0.12***	−0.12**
Chapter 7 liquidation		−0.19	−0.15	−0.05	−0.17
Dealer size			0.26***	0.26***	0.36***
Dealer centrality			−0.62***	−0.62***	−0.17***
Dealer inventory			−0.01*	−0.01	0.00
Retail	0.55***	0.52***	0.40***	0.41***	0.26***
LargeInstitutional	−0.18***	−0.22***	−0.12***	−0.12***	0.07***
Maturity		−4.78***	−4.40**	−2.67*	−1.20
Seasoning		−0.03**	−0.03*	−0.03*	−0.01
Issue size		−0.02	0.00	−0.01	0.03
Rating		−0.04	−0.04	−0.11	−0.13
Junk rated		−0.01	−0.02	0.04	0.08
Unrated		−0.11	−0.10	−0.15*	−0.06
Enhanced		0.02	0.04	0.02	0.05
Callable		−0.18***	−0.19***	−0.16***	−0.07**
Sinking fund		0.09	0.12*	0.10	0.22**
Senior unsecured		0.01	0.00	0.00	0.05
Senior subordinate		−0.04	−0.05	−0.06	0.01
Subordinate junior		0.07	0.02	0.02	0.15
Coupon		0.01	0.00	0.01	−0.01
CDS availability		−0.14***	−0.11***	−0.12***	−0.08**
Covenants		0.05	0.06	0.05	−0.01
Bond FE	Yes	No	No	No	No
Dealer FE	No	No	No	No	Yes
# observations	625,548	625,548	625,548	625,548	625,548

risk their own capital for intermediating defaulted bonds for which they had handled most of the order flow prior to default. Moreover, the negative interaction effects in specifications 4 and 5 show that primary dealers are even more likely to act as principals once a bond defaults. As one would expect, primary dealers are more likely to take bonds into inventory, likely because they are familiar with the bond, and the potential investor universe, and are thereby able to better manage the risk of ownership than other dealers. Complementing the findings of Goldstein and Hotchkiss (2020) who show that central dealers are more likely than peripheral dealers to provide inventory capacity, we find that primary dealers are more likely to take defaulted bonds into their inventory than other dealers. We furthermore find a significant positive effect of dealer size on the probability of trading as a broker.

3.3 Complexity of matching

We estimate whether default events have an impact on the probability of dealers selling bonds on the same day as acquired, instead of keeping them in inventory overnight. Here, we consider all 625,548 client-to-dealer and consecutive offsetting trades observed during the year before default and until 30 days thereafter. More formally, we apply a Probit model that estimates whether a dealer sells a bond that they recently acquired from one of their clients through a consecutive dealer-to-client trade (*CDC* round-trip) or dealer-to-dealer trade (*CDD* trade chain) on the same day ($\mathit{IntraDayMatch}_{ij} = 1$), or whether the dealer keeps the bond in inventory overnight ($\mathit{IntraDayMatch}_{ij} = 0$):

$$\begin{aligned}\Pr(\mathit{IntraDayMatch}_{ij} \mid \mathit{Trade}_{ij}^{CD}) = \Phi(&\alpha_0 + \alpha_1\, \mathit{PostDefault}_{ij} \times \mathit{PrimaryDealer}_{ij} + \\ &+ \alpha_2\, \mathit{PostDefault}_{ij} + \alpha_3\, \mathit{PrimaryDealer}_{ij} + \beta'\, X_{ij}). \quad (16)\end{aligned}$$

Variable definitions are similar to those used in specification (14). Additionally, we include an interaction term between $\mathit{PostDefault}_{ij}$ and $\mathit{PrimaryDealer}_{ij}$ in the baseline specification. We adjust standard errors for heteroskedasticity and cluster by bond issue and time.

Table 8 shows the regression results. We find in specifications 1–3 that dealers are significantly less likely to sell a recently defaulted bond on the same day as acquired, compared to bonds that have not yet defaulted. This finding demonstrates that dealers are indeed more

Table 8: **Intra-day matches before and after default.** Probit regression for the probability of dealers matching a client-to-dealer trade with a consecutive buyer on the same day. The dependent variable indicates 1 if the dealer sells the bond to the next buyer on the same day as acquired from the client, and 0 if the bond remains in the dealer's inventory at the end of the day. Buyers may be clients or other dealers. A total of 625,548 (494,050 pre-default and 131,498 post-default) client-to-dealer trades are considered, of which 331,315 (276,193 pre-default and 55,122 post-default) are matched with either dealer-to-client trades (*CDC* round-trip) or dealer-to-dealer trades (*CDD* trade chain) on the same day. The *PostDefault* dummy variable indicates whether a trade takes place after the default event. *PrimaryDealer* indicates whether the bond is sold to the primary dealer. The explanatory variables further include dealer characteristics, default event type, trade characteristics, bond characteristics, and year fixed effects. Non-binary explanatory variables are normalized with center 0 and standard deviation 1. Standard errors are adjusted for heteroskedasticity and clustered by issue and time. Significance is denoted *** (1%), ** (5%), and * (10%).

	$\Pr(IntraDayMatch_{ij})$				
Specification	(1)	(2)	(3)	(4)	(5)
$PostDefault \times PrimaryDealer$				−0.79***	−0.97***
$PostDefault$	−0.20***	−0.24***	−0.22***	−0.09***	−0.08**
$PrimaryDealer$	−0.55***	−0.64***	−0.62***	−0.46***	−0.08
Distressed exchange		−0.19***	−0.20***	−0.18**	−0.14**
Risk rating		−0.18***	−0.20***	−0.18***	−0.13**
Chapter 11		−0.21***	−0.24***	−0.22***	−0.18***
Chapter 7 liquidation		−0.40***	−0.35**	−0.29**	−0.37**
Dealer size			0.08***	0.08***	0.15***
Dealer centrality			−0.32***	−0.33***	−0.06**
Broker role			1.61***	1.58***	1.49***
Dealer inventory			−0.02***	−0.02***	−0.01**
Retail	0.05*	0.08***	−0.26***	−0.25***	−0.31***
LargeInstitutional	0.26***	0.19***	0.34***	0.33***	0.54***
Maturity		−0.03*	0.00	0.01	0.02
Seasoning		−0.01	0.01	0.01	0.01
Issue size		−0.05***	−0.06***	−0.07***	−0.04*
Rating		−0.04*	−0.05**	−0.07***	−0.06**
Junk rated		−0.10	−0.13*	−0.08	−0.06
Unrated		−0.26***	−0.29***	−0.32***	−0.24***
Enhanced		−0.02	−0.03	−0.05	0.02
Callable		−0.18***	−0.13***	−0.11***	−0.01
Sinking fund		−0.06	−0.10	−0.10	−0.11
Senior unsecured		0.01	0.01	0.01	0.01
Senior subordinate		−0.08*	−0.09*	−0.09*	−0.10**
Subordinate junior		−0.06	−0.13**	−0.13**	−0.15**
Coupon		0.05***	0.05***	0.05***	0.03**
CDS availability		−0.16***	−0.11***	−0.11***	−0.02
Covenants		−0.07**	−0.12***	−0.12***	−0.07**
Bond FE	Yes	No	No	No	No
Dealer FE	No	No	No	No	Yes
# observations	625,548	625,548	625,548	625,548	625,548

likely to keep bonds that recently defaulted in overnight inventory at the end of the day on which clients offload their bonds to the dealers. Thus, dealers commit their capital by taking these defaulted bonds in overnight inventory. The results show that primary dealers are more likely to take bonds in overnight inventory than non-primary dealers, and the significant and negative interaction between the primary dealer indicator and the post-default dummy variable in specifications 4 and 5 indicates that the likelihood of primary dealers utilizing overnight inventory increases significantly more for them once a bond defaults.

Dealers absorb client sell orders depending on the severity of the default event type, with distressed exchanges and risk rating downgrades showing the smallest, and Chapter 7 liquidations showing the largest significant effects. Thus, dealers are more likely to keep bonds of the most severe default event type in inventory overnight. When dealers act as brokers, the likelihood of them offsetting trades on the same day is significantly higher, which corresponds to the broker role of dealers without utilizing their own inventory. This is reasonable, given that dealers prearrange trades when they act as brokers. Moreover, when dealers have accumulated bond inventories over the recent month, indicated by dealer inventory, the likelihood of putting additional bonds into inventory is significantly lower, highlighting constraints in dealer inventory that impede additional risk-taking. In general, our analysis shows that dealers, particularly primary dealers, are more likely to keep recently defaulted bonds in inventory overnight rather than sell them to another counterparty on the same day.

3.4 Inventory risk taking

We now explore dealers' role in facilitating transactions of defaulted bonds by providing inventory capacity, and potentially conducting proprietary trading in defaulted bonds. In subsection 3.3 we have shown that dealers are more likely to take a bond in overnight inventory after its default event than before it. Dealers thus commit their capital to trades, facilitating the timely execution of bondholders' sale orders. After committing capital for placing bonds in overnight inventory, a dealer may sell the bond to another client or dealer on

Table 9: **Dealers' aggregate inventory in bonds one day before their default and 30 days thereafter.** The dealer inventory is denoted in the percentage of a bond's par value that is held on dealers' balance sheets and is a relative measure that tracks net additions to and subtractions from dealers' inventories relative to the inventory levels one year prior to default.

	N	*Mean*	*SD*	*q5*	*q25*	*q50*	*q75*	*q95*
Dealer inventory before default	2,474	1.7%	8.5%	-8.1%	-0.6%	0.8%	3.7%	14.8%
Dealer inventory after 30 days	2,474	2.6%	9.8%	-8.4%	-0.6%	1.2%	5.1%	18.2%
Difference		0.9%***						

the next day, or several days later, provided that a counterparty is found. Thereby, the dealer eliminates their idiosyncratic exposure to the defaulted bond, but in cases when the bond is sold to another dealer, the collective dealers' commitment to a defaulted bond's par value will remain constant. We are interested in knowing whether, and to which degree, dealers collectively commit capital to compensate for a mismatch in market supply and demand triggered by a bond's default event and to bridge the gap between bondholders' sales and the time high-valuation buyers are found, we analyze dealers' net inventory positions in defaulted bonds. That is, we examine whether dealers collectively absorb investors' selling pressure induced by corporate bond default events.

As bond dealers do not disclose inventory levels or the amount of capital they put at risk in individual bonds, we use a relative measure of inventory that tracks changes in inventory from a fixed reference date, following the methodology of Bessembinder, Jacobsen, Maxwell, and Venkataraman (2018). Details for constructing inventories are provided in Appendix A.

Table 9 reports summary statistics of dealer inventories. Here, the reference date is one year prior to default and the inventory is reported relative to this reference date. Compared to the day before default, dealers additionally accumulate an average of 0.9 percentage points of a defaulted bond's par value during the 30-day period after default, which is significant at the 1% level. While the table shows that dealers even reduce inventories in some cases, dealers accumulate more than 5.1% of par value for one-quarter of all defaulted bonds during the

30-day period after default. Hence, dealers' collective capital commitment has an important effect on the liquidity provision of recently defaulted bonds. As the inventory buildup prior to default further demonstrates, dealers absorb selling pressure even when the bond has not yet defaulted. This evidence is consistent with dealers working harder to intermediate defaulted bonds.

Next, we investigate the post-default efficiency of defaulted bond prices.

4 The Price-Stabilizing Role of Primary Dealers

The defaulted-bond setting is unique in that dealers have to both counterbalance selling pressure and at the same time find high-valuation buyers, e.g., specialized vulture investors that can reap high recoveries in post-default negotiations. To check whether primary dealers counterbalance the negative price impact from selling pressure during default and trade with higher-valuation buyers at more information-efficient prices, we investigate how trading with primary dealers affects price reversals after default.

We measure the bond price rebound between observed recovery prices in transactions of investors who sell immediately after default (i.e., within the 30-day post-default period) and subsequent prices observed when the surprise element of default has already faded. As we intend to capture only prices that relate to investors' recovery, we again consider only client-to-dealer sale transactions. As such, we do not include prices paid between dealers or by investors. Furthermore, we focus on the short-term price appreciation rather than long-term effects, as we intend to identify the primary dealers' stabilizing effect related to the default surprise which is likely to vanish shortly after the initial supply shock. Because prices may still fluctuate even after the default surprise has vanished, we consider a relatively short 10-day window at the beginning of the second month after the default for measuring the pricing of client-to-dealer trades likely unaffected by the initial price pressure.[22]

We define price appreciation $PriceRebound_{ij}$ as bond j's price difference in a client-to-dealer transaction i during the 30 days after default, and the mean daily prices paid in client-to-dealer transactions from 31 to 40 days after default:

$$PriceRebound_{ij} = \frac{1}{T+1} \sum_{s=t}^{t+T} \left(\frac{1}{|K_{js}|} \sum_{k \in K_{js}} RR_{kj} \right) - RR_{ij}, \tag{17}$$

where K_{js} is the number of trades in bond j on day s, starting 31 days after default, day t, until 40 days after default. $PriceRebound_{ij}$ thus captures the percentage points of a bond's par value that an investor who sells immediately after default forgoes, rather than holding the bond until the second month after default. We estimate how investors' decision to trade with a primary dealer affects the observed price differences between the two time periods. More specifically, we employ the following specification for estimating post-default bond price appreciation:

$$PriceRebound_{ij} = \alpha + \rho \, \widehat{PrimaryDealer}_{ij} + \beta' \, X_{ij} + \epsilon_{ij}, \tag{18}$$

where $PriceRebound_{ij}$ is the price difference as defined in (17). The control variables are similar to those used in (6). Here, a total of 106,992 post-default client-to-dealer trades are considered. To account for a heterogeneous response, we also consider the selection-adjusted specification (9), but with $PriceRebound_{ij}$ as a dependent variable:

$$PriceRebound_{ij} = \alpha + \rho \, PrimaryDealer_{ij} \times p_{ij} + \lambda \, K(p_{ij}) + \beta' \, X_{ij} + \epsilon_{ij}. \tag{19}$$

[22] Trading volume is still high in the second month after default, and most bankruptcies are unlikely to be resolved by then, allowing us to employ a comparable sample size for estimating primary dealers' effects on recovery rate. Furthermore, as claim holders typically enter negotiations shortly after default, prices in later periods may already reflect measures taken by the firm to resolve distress or new expectations about ultimate recovery.

Table 10: **Post-default price rebound.** The binary *PrimaryDealer* variable indicates whether the bond is sold to a primary dealer. The price appreciation *PriceRebound* is the dependent variable in specifications 1–5. Specifications 3–5 control for potential endogeneity, selection bias, and essential heterogeneity. A total of 106,992 post-default client-to-dealer trades are considered for price appreciation estimation. Non-binary explanatory variables are normalized with center 0 and standard deviation 1. Standard errors are adjusted for heteroskedasticity and clustered by issue and time. Significance is denoted *** (1%), ** (5%), and * (10%).

	$PriceRebound_{ij}$				
	(1)	(2)	(3)	(4)	(5)
Specification	OLS	Saturated	IV	Heckman	MEH
PrimaryDealer ($\times p$ in (5))	−3.19***	−0.81*	−5.62***	−2.24**	−5.71***
Lambda				26.01***	
p					−16.76***
p^2					6.93***
LargeInstitutional	−0.79*	0.09	−0.63	−0.35	−0.30
Retail	0.26	−0.20	0.34	1.58***	1.55***
Distressed exchange	−21.58***	−21.40***	−20.80***	−18.80***	−18.94***
Risk rating	−17.39***	−17.40***	−16.62***	−15.05***	−15.09***
Chapter 11	−19.80***	−19.40***	−18.93***	−17.86***	−17.88***
Chapter 7 liquidation	−16.66***	−15.53***	−15.52***	−11.58**	−11.69**
Seniority FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Industry distress FE	Yes	Yes	Yes	Yes	Yes
Bond features	Yes	Yes	Yes	Yes	Yes
Liquidity features	Yes	Yes	Yes	Yes	Yes
Macroeconomic features	Yes	Yes	Yes	Yes	Yes
Company features	Yes	Yes	Yes	Yes	Yes
Dealer FE	No	Yes	No	No	No
R^2	0.4595	0.4956	0.4594	0.4663	0.4693
# observations	106,992	106,992	106,992	106,992	106,992

We expect more efficient prices and hence less price rebound due to the primary dealer's expertise. Given that bonds that are sold to primary dealers immediately following a default event achieve higher recoveries, the subsequent price reversal should be less pronounced for these transactions.

Results. Table 10 reports our results for five variants of specifications (18)/(19). The two columns to the left use the actual primary dealer indicator as an explanatory variable, without (specification 1) and with (specification 2) dealer fixed effects. Specification 3 considers the instrumented primary dealer indicator, specification 4 follows the self-selection correction approach of Heckman (1979), and specification 5 employs the model of essential heterogeneity. The instrument is created as in Table 3. As all five columns show, selling to primary dealers immediately after default is equivalent to counterbalancing temporary price pressure, given that the following price rebound is less pronounced for those trades routed via primary dealers. In specification 2, where we add dealer fixed effects, the primary dealers' effect remains negative, although at a smaller magnitude than the other specifications. This is in line with the presence of unobserved dealer-specific characteristics that are correlated with the primary dealer indicator. The Lambda in column 4 is significant, indicating the presence of selection bias in specifications 1–3. Finally, the specification that accounts for heterogeneity captures a similar effect of $PrimaryDealer$ on $PriceRebound$ as the other specifications, and it includes a significant non-linear term. Although slightly smaller, the estimated coefficients of $PrimaryDealer$ in Table 10 are of a similar magnitude as in the corresponding specifications in Table 3.

Overall, the primary dealer expertise coefficient δ in Table 3 and ρ in Table 10 show that trading with a primary dealer leads to higher and more stable recovery prices after default vis-à-vis prices observed once the initial default surprise has vanished. These findings suggest that the recovery benefits provided by primary dealers during the default-induced times of stress are permanent. This is consistent with being the result of their superior expertise, and it is not due to fire sale discounts or price pressures. These results also rule out market timing as an explanation behind the results on bond-level recovery rates. Overall, the evidence suggests that primary dealers stabilize distressed bond markets by offering higher, more stable, and informationally efficient prices than other dealers, which mitigates credit risk for existing investors.

5 Conclusion

While there exists an extensive literature on the intermediation of corporate bonds in good standing, little is known about the intermediation of defaulted corporate bonds. When a bond becomes distressed, its ownership has to consolidate and change from regular investors like pension funds and insurance companies to specialized vulture investors who are better at recouping higher recovery values and avoiding aggregate losses. We present a comprehensive body of evidence on the intermediation of defaulted corporate bonds.

Our empirical analysis shows that trading and intermediation patterns undergo significant changes after a bond's default, in that not all dealers transact in defaulted bonds, intermediation chains elongate, and a special type of dealer, which we term "primary dealer", intermediates much of the post-default order flow. Similar to the primary dealer system observed in government bond markets, investors direct their order flow to the bond's primary dealer(s) that have developed specialized intermediation expertise in valuing, handling, and placing that particular bond before its default and that intermediate defaulted bonds through longer intermediation chains and absorb selling pressure through their inventory.

The advantages for investors of transacting with primary dealers are both higher recovery rates and more informationally efficient prices, as they are closer to the bond's long-term value. Despite the drop in value for bonds in default, investors who sell to primary dealers realize recoveries of an extra \$4 to \$7 per \$100 invested, or more than 10% premium over the mean recovery rate. The higher recoveries are accompanied by more stable post-recovery bond prices and less price rebound. Trading with primary dealers thus results in better allocation efficiency as reflected in the improved recovery rates.

Primary dealers thus contribute to stabilizing the distressed bond market's functioning and mitigating credit risk ex-ante by recouping higher recovery values for investors ex-post. These results are consistent with recent OTC market theories, including predictions by Glode and Opp (2019) and Chaderina and Glode (2023) that dealers', and in our case primary dealers', expertise leads to better allocation efficiency and by Glode and Opp (2016) that longer intermediation chains weaken traders' incentives to screen counterparties thus reducing the adverse selection and increasing trade efficiency.

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Appendix A Sample Construction and Methodology

Explanatory variables. The empirical studies on dealer intermediation in defaulted bonds and recovery rates incorporate various explanatory variables. We add information from FISD that is directly associated with the bond issue, such as offering amount, days to maturity at default, coupon rate, covenant information, and bond ratings one year prior to default. We encode ratings as integers, starting with AAA=1, AA+ =2, and so forth. The availability of CDS contracts is retrieved from S&P Capital IQ. From S&P Capital IQ, we also collect point-in-time firm information that represents issuers' characteristics and financials most recently available prior to default. This includes equity value, the number of employees, and both short and long-term debt in order to replicate the default barrier as employed by Jankowitsch, Nagler, and Subrahmanyam (2014) as a proxy for structural credit risk.[1]

We furthermore collect information on pre-default bond ownership from eMAXX data. We retrieve GDP and the slope of the interest yield curve from the Federal Reserve Economic Database of the Federal Reserve Bank of St. Louis (FRED), and we construct the 90-day corporate bond default rate derived from our defaulted bond data and the Transaction Reporting and Compliance Engine (TRACE). We collect industry-specific data about stock indices growth and industry-wide sales growth from S&P Capital IQ for creating industry distress measures similar to those employed by Acharya, Bharath, and Srinivasan (2007). Post-default bond liquidity, similar to that used by Jankowitsch, Nagler, and Subrahmanyam (2014), is calculated with bond transaction data from TRACE.

Dealer network and transaction data. The academic version of TRACE data that we utilize covers actual bond transactions that were executed during the sample period.[2] This

[1] We consider a firm's market value of equity when available, and book value of equity reported in the most recent company filings prior to default in cases where the market value of equity is not available.

[2] The TRACE data contain a few thousand observations of transactions executed prior to 2004, which may be the result of lagged transaction reports to TRACE. We drop all of these transactions which were not executed prior to 2004.

data includes comprehensive transaction information, including time stamps, the transactions' par amounts, executed prices, unique CUSIP identifiers for each bond, and, most notably, unique masked identifiers for all dealers involved in the transactions. The dealers' clients are uniformly labeled 'C' without further information about their (masked) identities. The aforementioned characteristics of the data allow us to precisely trace individual bonds as they circulate from clients to dealers, between dealers, and from dealers to clients. Before incorporating data from TRACE into the sample construction, we preprocess the data in order to eliminate known flaws in the data by implementing the standard data cleaning methodologies described by Dick-Nielsen and Poulsen (2019). We first apply a basic transaction filter which removes transactions from TRACE data where a trading sequence of multiple transactions with identical execution prices was reported and which represents an introducing dealer interacting with the executing dealer as an agent on behalf of a client. Note that we also apply a filter to remove erroneous transaction reports from TRACE as suggested by Dick-Nielsen and Poulsen (2019), and further follow Jankowitsch, Nagler, and Subrahmanyam (2014) in applying a price filter to remove potentially falsely reported prices for recovery rate calculation. The cleaned data set contains 114,584,837 reported transactions, involving 107,088 distinct instruments. We match the cleaned TRACE data to FISD based on the instruments' unique CUSIP identifiers and drop all transactions that involve instruments that are not covered by FISD.[3]

After this step, our data includes 108,895,440 reported transactions of 88,156 distinct debt instruments. Given the masked dealer identifiers linked to the transactions recorded in TRACE, we are able to identify unique dealers and track inter-dealer trade relationships within the data. In total, 3,407 unique dealers intermediate bonds in the data sample. 40.5% of the transactions represent inter-dealer transactions whereas 25.3% of the transactions

[3] Cross-checking with S&P Capital IQ reveals that the majority of the dropped data refers to instruments issued by foreign entities.

are client-to-dealer transactions and 34.2% are dealer-to-client transactions. Of the 3,407 dealers, 80% are directly interacting with clients, and 20% are solely intermediating bonds between other dealers. 3,383 of the dealers interact with other dealers, whereas 24 dealers only interact with clients but not with other dealers. We remove these dealers for creating the dealer network as they are not connected to it and they represent only a negligibly small number of transactions. We then follow the methodology outlined by Li and Schürhoff (2019) in creating two alternative dealer network representations. The equal-weighted dealer network solely indicates the existence of a transaction relationship between two dealers and the trades-weighted variant weighs links by the number of transactions executed between dealers.

From the dealer network representations, we compute dealer centrality measures. The descriptive statistics for degree, in-degree, out-degree, eigenvector (Bonacich, 1972), betweenness (Freeman, 1977), closeness, as well as in-closeness and out-closeness (Bavelas, 1950) centrality are shown in Table A.1. Di Maggio, Kermani, and Song (2017) report a core-periphery structure of the corporate bond dealer network, which we confirm and refer to Figure A.1 for an illustration of the non-randomness in dealer connectedness based on in- and out-degree centrality.

For the purpose of our empirical analysis, we use 1-year monthly trailing dealer networks to determine dealers' centralities. We drop all 124 bonds that defaulted before 2005 for which we don't have a complete year of trading data to create the dealer network prior to default. Furthermore, for comparing bond-level characteristics between pre- and post-default trading periods, we only consider bonds for which we have trading data in both periods. We also only consider those transactions in which dealers act as buyers, yielding a data set that comprises 2,446 bonds for comparing dealer centralities. During the year prior to default, each of these bonds is bought by an average (median) of 53 (39) unique dealers, and during the 30-day period after default by an average (median) of only about

Table A.1: Summary statistics of dealer centralities in the corporate bond dealer network. The network is constructed with transaction information reported to the Transaction Reporting and Compliance Engine (TRACE) and represents 44,065,910 inter-dealer transactions. In the network, 3,383 bond dealers that have transaction relationships with other dealers are represented as nodes. Panel A shows summary statistics of dealer centrality measures derived from an equal-weighted variant of the network in which links have binary weights that indicate if two dealers traded with each other. Panel B shows summary statistics of centrality measures derived from a trades-weighted variant of the network in which links are weighted by the number of transactions between two dealers. Both Panel A and Panel B formally describe a core-periphery network structure in which few dealers are located centrally in the network, while most dealers are located in the network's periphery.

	SD	***q25***	***q50***	***Mean***	***q75***	***q95***	***Max***
Panel A: Equal-weighted network							
Degree	0.04	0.00	0.00	0.02	0.01	0.09	0.40
In-degree	0.04	0.00	0.00	0.01	0.01	0.08	0.36
Out-degree	0.04	0.00	0.00	0.01	0.01	0.08	0.37
Eigenvector	0.17	0.01	0.02	0.10	0.10	0.50	1.00
Betweenness	0.00	0.00	0.00	0.00	0.00	0.00	0.09
Closeness	0.05	0.37	0.40	0.41	0.45	0.51	0.62
In-closeness	0.13	0.35	0.38	0.36	0.43	0.49	0.60
Out-closeness	0.07	0.34	0.36	0.36	0.40	0.46	0.57
Panel B: Trades-weighted network							
Degree	55.11	0.01	0.05	7.70	0.50	14.09	1,446.46
In-degree	29.88	0.00	0.02	3.85	0.25	7.01	1,008.83
Out-degree	26.59	0.00	0.03	3.85	0.23	7.50	544.56
Eigenvector	0.02	0.00	0.00	0.00	0.00	0.00	1.00
Betweenness	0.00	0.00	0.00	0.00	0.00	0.00	0.05
Closeness	0.00	0.02	0.03	0.02	0.03	0.03	0.03
In-closeness	0.01	0.03	0.03	0.02	0.03	0.03	0.03
Out-closeness	0.02	0.07	0.07	0.07	0.08	0.08	0.08

20 (11) dealers, indicating a concentration of trading activity in recently defaulted bonds on fewer dealers. This observation suggests that recently defaulted bonds are intermediated by a smaller group of dealers than before the default event, likely because investors switch to more expert dealers, such as primary dealers, after default.

Determining agency trades. For each bond transaction reported in TRACE data, an indicator denotes agency trades in which dealers prearrange the trades in a broker role without taking inventory risk. These agency trades represent about 8% of all transactions reported to TRACE in our data. However, as a standard convention in the literature,

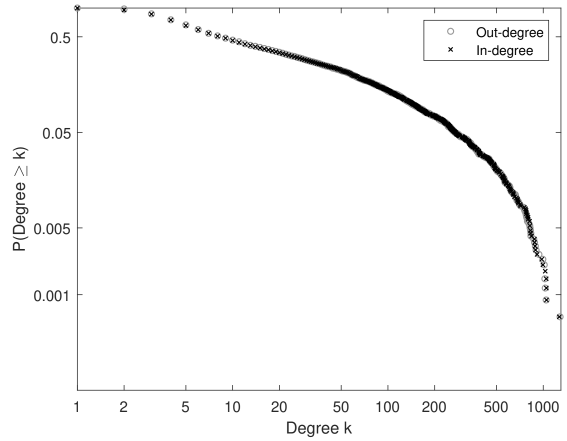
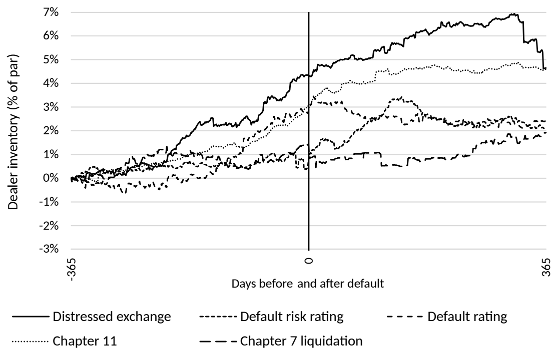


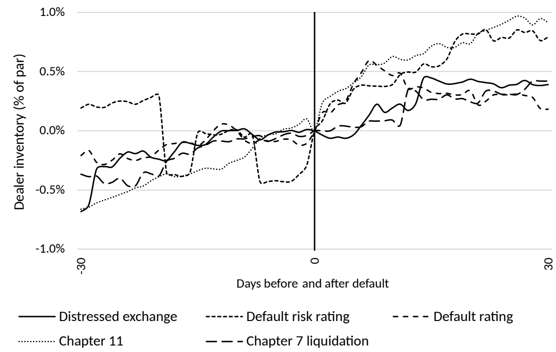
Figure A.1: The figure illustrates the inverse in- and out-degree centrality distribution of the 3,383 bond dealers that form the dealer network. Out-degree centrality is represented by circles and in-degree centrality by cross-marks. The figure is log-scaled and shows that the centrality distribution is right-skewed, with a large number of dealers that maintain only a few trade relationships, and a small number of dealers that maintain many trade relationships.

principal trades that are offset within one minute after the dealer purchased the bond are also considered prearranged riskless trades, as it is likely that these client-to-dealer trades are only executed after a dealer searched and found a trade counterparty to immediately offset the position. Hence, we follow this convention and denote all client-to-dealer trades that are offset by consecutive dealer-to-dealer or dealer-to-client trades of the same par amount within one minute as prearranged agency trades, in line with Bessembinder, Jacobsen, Maxwell, and Venkataraman (2018), Bao, O'Hara, and Zhou (2018), and Li and Schürhoff (2019). It may occur that a dealer splits the trade after the purchase, selling the bonds to several buyers. We account for splits of up to three separate offsetting trades. Using this broader definition to identify dealers' riskless trades, 36% of the trades in the data are trades in which dealers act as brokers, and 64% of the trades are principal trades. This differs from Bessembinder, Jacobsen, Maxwell, and Venkataraman (2018), who report about 90% of trades in TRACE in our sample are principal trades. However, they only consider the top 10–12 dealers that correspond to about 70% of total trading volume in TRACE, whereas we include all dealers in our analysis. When we only consider trades performed by the top 12 dealers, we find that these account for about 67% of the total USD trading volume, for which only 11% of the client-to-dealer trades are agency trades, comparable to the characteristics of the transaction data sample employed by Bessembinder, Jacobsen, Maxwell, and Venkataraman (2018). In our empirical analysis, we consider this definition of agency trades in order to distinguish the role of dealers in intermediating defaulted bonds.

Determining dealer inventory. Actual levels in dealer inventories for specific bonds are not observable. Hence, we create inventory measures that reflect dealers' collective inventory additions and subtractions in defaulted bonds from a normalized reference point based on transactions observed in TRACE. We offset all client-to-dealer trades with all dealer-to-client trades on each day for a given bond. Alternatively, we consider the date when the bond's outstanding amount in FISD is set to zero as the date that the bond ceases to exist. This happens in only a few cases shortly after the default event, and we offset the whole inventory for a given bond to zero in these cases. We define the residual as the dealers' collective net inventory change in a given bond. In order to not distort variations in inventory due to price fluctuations, we consider trade volume in par amount for accumulating and offsetting positions. In dealer-to-dealer trades, the inventory of the buyer-dealer will increase by the same amount that the inventory of the seller-dealer decreases, hence, a net effect of zero on the dealers' collective inventory will be recorded in dealer-to-dealer trades. We compute dealer inventory on a daily basis over the pre- and post-default periods for each bond, that is the year before default until 30 days after default. As no starting inventory is known, we may index the collective dealers' inventory for each bond at 0 on a reference date. The daily inventory measure thus reflects deviations from this starting inventory. Figure A.2 illustrates the collective dealer inventory in defaulted bonds by default event type with reference dates



(A) Collective dealer inventory, indexed at zero one year before the default event.



(B) Collective dealer inventory, indexed at zero on the day of the default event.

Figure A.2: Collective average dealer inventory in defaulted firms' bonds, distinguished by default event type. The dealer inventory is calculated as the average par value of all bonds of a firm that dealers hold on their balance sheet and is fixed at 0 one year before default in Panel A and after default including the default day itself in Panel B. After removing default events of the years 2004 and 2016, and 7 outlier firms, 629 firm-default observations involving 2,338 bonds that defaulted between January 2005 and December 2015 are considered.

one year prior to default (Panel A) and on the default day (Panel B), respectively.

Appendix B Trade-Based Recovery Rates

Table 3 reports the regression results for trade-level recovery rates. In order to control for potential endogeneity, selection bias, and essential heterogeneity, we use several IV approaches. The pre-default ownership concentration among institutional investors serves as the instrument to proxy for a supply shock that drives trading with primary dealers.

To check robustness, we introduce alternative instruments in Tables B.1 and B.2. Table B.1 utilizes the pre-default number of different investor types from eMAXX as an instrument. In the first-stage regression shown in the left column, the instrument is negatively related to trading with primary dealers. It captures that if the pre-default ownership in a given bond is dispersed enough among a variety of different investor types, the post-default shift to primary dealers found in Table 2 will be attenuated, given the heterogeneity in investors' selling or holding motives. Table B.2 implements an instrument that follows a comparable approach, but employs the total number of individual investors rather than the number of investor types. Both tables confirm our findings on the trade-level recovery rate.

Table B.1: **Trade-based recovery rates—alternate instrument 1.** The left column is the Probit specification that estimates the probability of clients trading with primary dealers when selling recently defaulted bonds in order to create the instrumental $PrimaryDealer$ variable. The binary $PrimaryDealer$ variable indicates whether the bond is sold to a primary dealer. The recovery rate $RecoveryRate$ is the dependent variable in specifications 1–5. Specification 2 controls for dealer-specific effects. Specifications 3–5 control for potential endogeneity, selection bias, and essential heterogeneity. A total of 108,536 post-default client-to-dealer trades are considered for recovery rate estimation. Non-binary explanatory variables are normalized with center 0 and standard deviation 1. Standard errors are adjusted for heteroskedasticity and clustered by issue and time. Significance is denoted *** (1%), ** (5%), and * (10%).

	$PrimaryDealer_{ij}$	Trade-level recovery rate RR_{ij}				
		(1)	(2)	(3)	(4)	(5)
Specification	1st stage	OLS	Saturated	IV	Heckman	MEH
$PrimaryDealer$ ($\times p$ in (5))		4.52***	2.03***	5.98***	3.76***	7.32***
Lambda					−21.43*	
p						−6.89
p^2						14.80*
Pre-default no. of investor types	−0.08***					
LargeInstitutional	0.15	−0.23	−1.22**	−0.35	−0.62	−0.53
Retail	0.51***	−0.24	0.25	−0.23	−1.30*	−0.36
Distressed exchange	1.08***	12.36***	11.63**	11.60**	9.94*	12.23**
Risk rating	0.92***	14.32***	14.50***	13.50***	12.19**	13.73***
Chapter 11	0.70***	−2.05	−2.31	−3.03	−3.77	−2.50
Chapter 7 liquidation	1.21	0.90	0.00	−0.09	−2.18	0.19
Seniority FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry distress FE	Yes	Yes	Yes	Yes	Yes	Yes
Bond features	Yes	Yes	Yes	Yes	Yes	Yes
Liquidity features	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic features	Yes	Yes	Yes	Yes	Yes	Yes
Company features	Yes	Yes	Yes	Yes	Yes	Yes
Dealer FE	No	No	Yes	No	No	No
R^2		0.5959	0.6185	0.5929	0.5974	0.6009
# observations	108,536	108,536	108,536	108,536	108,536	108,536

Table B.2: **Trade-based recovery rates—alternate instrument 2.** The left column is the Probit specification that estimates the probability of clients trading with primary dealers when selling recently defaulted bonds in order to create the instrumental *PrimaryDealer* variable. The binary *PrimaryDealer* variable indicates whether the bond is sold to a primary dealer. The recovery rate *RecoveryRate* is the dependent variable in specifications 1–5. Specification 2 controls for dealer-specific effects. Specifications 3–5 control for potential endogeneity, selection bias, and essential heterogeneity. A total of 108,536 post-default client-to-dealer trades are considered for recovery rate estimation. Non-binary explanatory variables are normalized with center 0 and standard deviation 1. Standard errors are adjusted for heteroskedasticity and clustered by issue and time. Significance is denoted *** (1%), ** (5%), and * (10%).

	$PrimaryDealer_{ij}$	Trade-level recovery rate RR_{ij}				
		(1)	(2)	(3)	(4)	(5)
Specification	1st stage	OLS	Saturated	IV	Heckman	MEH
$PrimaryDealer$ ($\times p$ in (5))		4.52***	2.03***	6.55***	3.86***	7.28***
Lambda					−19.66	
p						−12.24
p^2						19.19*
Pre-default no. of holders	−0.14**					
LargeInstitutional	0.16	−0.23	−1.22**	−0.36	−0.60	−0.45
Retail	0.51***	−0.24	0.25	−0.24	−1.22	−0.08
Distressed exchange	1.00***	12.36***	11.63**	11.65**	10.12*	12.77**
Risk rating	0.78***	14.32***	14.50***	13.60***	12.35**	14.13***
Chapter 11	0.58***	−2.05	−2.31	−2.98	−3.65	−2.17
Chapter 7 liquidation	1.13	0.90	0.00	−0.12	−2.03	0.87
Seniority FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry distress FE	Yes	Yes	Yes	Yes	Yes	Yes
Bond features	Yes	Yes	Yes	Yes	Yes	Yes
Liquidity features	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic features	Yes	Yes	Yes	Yes	Yes	Yes
Company features	Yes	Yes	Yes	Yes	Yes	Yes
Dealer FE	No	No	Yes	No	No	No
R^2		0.5959	0.6185	0.5940	0.5970	0.6011
# observations	108,536	108,536	108,536	108,536	108,536	108,536