Life after default: How dealer intermediation improves default recovery

FRIEDRICH BAUMANN ALI KAKHBOD DMITRY LIVDAN

ABDOLREZA NAZEMI NORMAN SCHÜRHOFF*

November 30, 2024

*We thank Stefano Colonnello, Maria Chaderina, Robert Czech, Jens Dick-Nielsen, Peter Feldhütter, Edith Hotchkiss, Amir Kermani, Gergana Jostova, Florian Nagler, Giorgio Ottonello, Loriana Pelizzon, Alex Philipov, Pierre-Olivier Weill and numerous seminar and conference participants for helpful comments. Friedrich Baumann is with the School of Economics and Management, Karlsruhe Institute of Technology, Germany. e-mail: friedrich.w.baumann@gmail.com. Ali Kakhbod is with the Walter A. Haas School of Business, University of California, Berkeley, USA. e-mail: akakhbod@berkeley.edu. Dmitry Livdan is with the Walter A. Haas School of Business, University of California, Berkeley, USA. e-mail: livdan@haas.berkeley.edu. Livdan is a Research Fellow of the CEPR. Abdolreza Nazemi is with the School of Economics and Management, Karlsruhe Institute of Technology, Germany. e-mail: nazemi@kit.edu. Norman Schürhoff is with the Faculty of Business and Economics and Swiss Finance Institute, University of Lausanne, CH-1015 Lausanne, Switzerland. e-mail: norman.schuerhoff@unil.ch. Schürhoff is a Research Fellow of the CEPR.

Life after default: How dealer intermediation improves default recovery

Abstract

We document that the intermediation of defaulted bonds impacts recovery values. After a bond defaults, trading intensifies and becomes concentrated among the bond's primary pre-default dealer. Intermediation by the primary dealer leads to a 4-7% improvement in the bond's recovery value relative to par. This effect is consistent with improved beliefs about recovery, driven by the primary dealer's reallocation of defaulted bonds to specialized distressed bond investors creating a positive feedback loop where prices in earlier transactions influence subsequent ones. Our findings suggest that dealer intermediation is crucial in stabilizing distressed-bond markets and mitigating credit risk for bondholders.

JEL Classification: G12, G14, G24

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

Distress significantly alters the investment characteristics and risk profile of corporate bonds, leading to a shift in ownership from traditional holders—such as insurance companies, pension funds, and mutual funds[1]—to more specialized investors like hedge funds and distressed bond investors (Ivashina, Iverson, and Smith, 2016; Feldhütter, Hotchkiss, and Karakaş, 2016). Distressed bond or vulture investors are known for their active involvement in restructuring efforts, often participating directly in firm-level activities aimed at enhancing the value of debt claims (Wruck, 1990; Hotchkiss and Mooradian, 1997; Jiang, Li, and Wang, 2012; Lim, 2015).[2] However, because corporate bonds are traded in decentralized over-the-counter (OTC) markets, this transition is not without frictions and dealers play a crucial role in facilitating the matching of forced sellers with expert buyers. Despite the importance of these dynamics for corporate recovery from distress, little is known about how vulture investors acquire positions in distressed corporate debt, the role dealers play in this process, and how the intermediation of defaulted bonds influences recovery values.

We use hand-collected data on 2,425 distressed corporate bonds issued by 498 unique U.S. firms to show that a predominant role in the intermediation of distressed corporate bonds belongs to primary dealers.[3] We designate the dealer who intermediates the largest number of trades in the bond during the year before the distress event as the bond's primary dealer.[4] Primary dealers handle on average 17% of the order flow before a bond becomes distressed, making them bond-central and experienced in intermediating 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. However, the bond's primary dealer is generally distinct from the most central dealer(s) in the overall dealer network.

We show that when the trading volume in the firm's bonds spikes during corporate distress the dealers' trading network adjusts to handle the abnormal trading activity and accommodate the shift in ownership by increasing the concentration of intermediation. While multiple dealers intermediate bonds in good standing, post distress, non-primary dealers

[1] Based on eMAXX data, the ownership share of mutual funds, which averages around 25% pre-default, declines to about 12% post-default.

[2] Post-default restructuring often results in improved operating performance relative to pre-default levels, especially when vulture investors gain control of the distressed firm (Hotchkiss and Mooradian, 1997).

[3] While the term "primary dealer" is most commonly associated with government bond markets—often referred to as "primary dealer markets"—it signifies a dealer likely involved in the bond's original issuance in the primary market and has remained a key participant in its secondary market. In the U.S. Treasury market, for example, primary dealers are financial institutions authorized by the U.S. Department of the Treasury to participate directly in Treasury securities auctions. This paper demonstrates that primary dealers also play an essential role in maintaining trading flow and liquidity in the corporate bond market.

[4] Our results are robust to alternate definitions for who is a primary dealer before the bond's default.

tend to reduce their intermediation of defaulted bonds, while primary dealers fill the gap by intermediating up to 40-50% of the turnover in distressed bonds. In addition, dealer centrality increases, intermediation chains become longer, and primary dealers act more in a principal role and take on larger inventory risk.

We then demonstrate that intermediation by primary dealers leads to better market outcomes. When trades are routed via primary dealers, trade-level recovery rates, measured as trade-level prices paid as a fraction of par value, increase by \$2 per each \$100 invested. Furthermore, bond-level recovery rates, measured as the average transaction price per par value, increase by \$6 per each \$100 invested. When we investigate how trading with primary dealers affects price rebound after a stress event, we find that investors who sell to primary dealers immediately after a stress event forgo up to \$5.6 per \$100 bond's par value less than investors who sell immediately after a stress event to other dealers forgo, as compared to holding the bond until the second month after a stress event. Thus, given that the subsequent price rebound is less pronounced for the trades routed via primary dealers, selling to primary dealers immediately after a stress event effectively counterbalances temporary price pressures. When combined with the results on market-based recovery rates, these findings show that trading with a primary dealer leads to higher and more stable recovery prices post-stress event vis-à-vis prices observed once the initial surprise has vanished.

The existing literature offers several potential explanations for why primary dealers provide better trade-level recoveries than other dealers. Primary dealers may have lower search and matching costs they may pass to clients via price improvement (Duffie, Garleanu, and Pedersen, 2005; Hugonnier, Lester, and Weill, 2019; Sambalaibat, 2022). Another potential explanation is that primary dealers may switch to riskless principal trades after default and thus may be 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). Finally, primary dealers may have lower inventory costs and pass some savings to clients as price improvement (Bessembinder, Jacobsen, Maxwell, and Venkataraman, 2018). However, all these price improvements are transitory and should lead to the same trade-level and bond-level recovery rates.

Motivated by empirical literature on the role of vulture investors in enhancing the value of distressed debt through restructuring (Wruck, 1990; Hotchkiss and Mooradian, 1997; Jiang, Li, and Wang, 2012; Lim, 2015; Huang, Lewellen, and Wang, 2024), we develop a simple model of intermediation in distressed corporate debt that connects trade-level price dynamics to bond-level restructuring outcomes. The model introduces two types of investors in

the distressed-bond market: specialized vulture investors and speculators. Vulture investors accumulate positions to strengthen their bargaining power in negotiating the bondholders' stake in the recovered value and to influence the restructuring of the debtor firm through active participation in firm-level activities. We assume that trading with vulture investors has two key effects. First, it enhances beliefs about the debtor firm's restructuring outcome and the bondholders' recovery value. This can also be interpreted as a premium in bond prices attributed to the value of creditor control, similar to the findings of Feldhütter, Hotchkiss, and Karakaş (2016), since trading through primary dealers increases creditor control. Second, it boosts confidence in the bondholders' ability to achieve a higher recovery on distressed debt, modeled through stronger persistence in positive beliefs resulting from trading with primary dealers. This increased confidence fosters more favorable terms in future transactions, creating a positive feedback loop that amplifies the initial positive impact.

In contrast, speculators purchase distressed bonds at low prices, aiming to profit from potential future price appreciations while free-riding on the efforts of vulture investors to improve bondholders' recovery. The reallocation of bonds from vulture investors to speculators weakens the former's ability to enhance bondholders' recovery, deteriorating beliefs about recovery outcomes and leading to less favorable future transactions. The belief about the recovery outcome thus varies with each transaction and is influenced by the history of previous transactions.

Primary dealers thus play a crucial role in the recovery process by possessing the bond-specific expertise to reallocate distressed bonds to specialized vulture investors and other experts (Glode and Opp, 2019; Chaderina and Glode, 2023). In contrast, non-primary dealers tend to redirect distressed bonds away from vulture investors and towards speculators who free-ride on the vulture investors' recovery efforts. To close the model, we assume that the transaction price is a linear combination of two factors: the direct price improvement—reflecting the extra value generated by primary dealers passing efficiency gains or cost savings to clients—and the belief about the bondholders' recovery.

The model solution confirms that the direct price improvement is transitory, contributing equally to both trade-level and bond-level recoveries when transactions involve primary dealers. However, the primary dealers' influence on the recovery belief component of prices is crucial for achieving higher bond-level recoveries compared to trade-level recoveries. The belief component of prices aggregates all changes resulting from past transactions, leading to a correlation between recovery rates and previous primary dealer transactions. As a result, the covariance between the bond-level average recovery rate and the average primary

dealer intermediation (captured by the aggregate primary dealer index) is greater than the sum of the covariances between trade-level recovery rates and trade-level primary dealer intermediation. This occurs because the latter does not account for the correlation between individual transactions, whereas the bond-level recovery incorporates the cumulative effect of past primary dealer activities.

We test for these additional model predictions in the data. To establish supporting evidence for the belief strengthening when trading with primary dealers, we add and interact a dummy variable to the trade-level recovery rate regression that indicates whether a trade in a defaulted bond takes place within 5 days after default with the primary dealer indicator, consistent with the spike in trading. In agreement with the model, we find that the effect of primary dealers on recovery rates magnifies immediately after default (in this case 5 days after default) as compared to later points in time during the 30 days after default. Trading with the primary dealer increases trade-level recovery by about twice as much, ($6.50 per $100 invested) immediately after default than later during the recovery process ($2.76 per $100 invested). We also find strong evidence supporting the feedback effect. Our results show that almost all improvements in trade-level recovery are from primary dealers creating a positive feedback loop from past transactions into the contemporaneous recovery rates.

Our results are hard to square with the standard informed trading hypothesis (Kyle, 1985; Babus and Kondor, 2018). In this case, we would expect that informed bond traders who trade through primary dealers push up prices and do so more over time, as the information that they accumulate positions slowly trickles into beliefs about bondholders' recovery. Then, the effect of primary dealers on recovery rates would magnify over time and would be smaller immediately after default compared to later points in time. However, we find the opposite in the data, consistent with the positive feedback loop hypothesis.

Our additional analysis focuses on better understanding the primary dealers' modus operandi. 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 intermediation chains are 7% shorter for primary dealers before the default but they are 11% longer for primary dealers than for other dealers post-default.[5] We next examine primary dealers' tendency to take bonds into inventory as opposed to prearranging trades in defaulted bonds in the role of a

[5]This finding is in line with the model of Glode and Opp (2016) where dealer intermediation chains help alleviate trade inefficiencies due to adverse selection. This mechanism falls under the direct price improvement channel in our model.

broker. We consider trades denoted as agency trades in TRACE and principal trades that are offset within one minute as agency trades. We show that primary dealers are significantly less likely to act as brokers once a bond defaults. This 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 before default and that primary dealers are even more likely to act as principals once a bond defaults.

Overall, the study highlights that the corporate bond market structure evolves endogenously. While neither TRACE transactions nor Refinitiv eMAXX ownership data identify both the seller and buyer in each transaction, we find support for dealers creating transactional value for sellers of distressed bonds and dealers also improving beliefs about recovery for buyers. After the bond's distress event, the ownership share of traditional institutional investors drops from 25% pre-default to 12% post-default. The intermediation of distressed bonds switches to primary dealers who locate distressed bond investors. These influence recovery via the restructuring process by participating in activities aimed at improving the value of their debt claims. Thus, primary dealers both provide an exit for investors facing selling pressure and, at the same time, improve efficiency by reallocating distressed assets to investors most capable of rebuilding their fundamentals.

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) examine the link between pre-default bond trading and the concentration and value of debt claims. Feldhütter, Hotchkiss, and Karakaş (2016) identify the value of creditor control in bond premia placed by activist bond investors in trades around bond default events. 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) and Dick-Nielsen, Poulsen, and Rehman (2023) 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 (Dick-Nielsen, Feldhütter, and Lando, 2012). 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 defaulted bonds in 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 relationship between the OTC market intermediation 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 thus linking between the market microstructure of the intermediation of the defaulted bonds and the debtor-firms-level restructuring.

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. Appendix A provides additional details on the sample construction.

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.[6] 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. This is done by utilizing 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, e.g., S&P's D rating, representing actual formal defaults.[7] 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.[8]

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

[7] 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.

[8] 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

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 days 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.[9]

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. Appendix A describes the TRACE data, data cleaning, and preparation of the dealer network in more detail. We match the default events with transaction data from TRACE in a 365-day window before default as the pre-default period during normal times, and a 30-day window after default. We define the default day as the event date and the 30 days after the default event 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.[10] The 30-day period for measuring default event-driven OTC trading patterns is in line with related event studies on bond market reactions.[11]

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.

[9] We take a similar approach in creating the set of defaulted bonds as Jankowitsch, Nagler, and Subrahmanyam (2014). Our approach differs as 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 years examined in this study while they 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 years that they analyze.

[10] The choice of 30 days 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.

[11] Ellul, Jotikasthira, and Lundblad (2011) use a 5-week period and Bao, O'Hara, and Zhou (2018) use 1

Table 1: **Trade summary statistics.** The TRACE data contains a total number of 108,895,440 trades. Therefore, 8.6% of trades are related to the 2,636 defaulted bonds, representing 8.6% of the total data. The year before default and the 30-day post-default period correspond to 1.8% and 0.3% of the trades, respectively, recorded in TRACE.

Sample	TRACE Total	Defaulted bonds Total	Defaulted bonds year pre-default	Defaulted bonds 30 days post-default
Dealer-to-customer trades	34.2%	30.9%	31.0%	19.2%
Customer-to-dealer trades	25.3%	27.5%	25.8%	41.4%
Dealer-to-dealer trades	40.5%	41.6%	43.2%	39.4%
Number of trades	108,895,440	9,336,290	1,956,480	315,292
% of TRACE	100%	8.6%	1.8%	0.3%

The sample for comparing the pre- and post-default periods comprises a total of 2,271,772 transactions in 2,636 defaulted bonds. Therefore, 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. The entire TRACE data sample contains more than 108 million trades of 88,156 bonds in total. 8.6% of trades are related to the 2,636 defaulted bonds. The year before default and the 30-day post-default period correspond to 1.8% and 0.3% of the trades, respectively. Thus, the 2,636 defaulted bonds represent a significant portion of all trading volume tracked in TRACE.

Table 1 reports summary statistics on the number of trades and prevalence of customer-to-dealer, dealer-to-customer, and dealer-to-dealer trades of defaulted and non-defaulted bonds in TRACE. As the table demonstrates, about 34% of the trades recorded in TRACE are dealer-to-customer trades, about 25% are customer-to-dealer trades, and about 41% are dealer-to-dealer trades. During the 30 days following a default event, dealer-to-customer trades decline to about 19%, and customer-to-dealer trades increase to about 41% of trades. Hence, customer-to-dealer trades gain in importance following a bond's default, presumably because dealers accommodate the excess supply.

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

month in their empirical studies on market reactions to corporate bond rating downgrades.

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 Defaulted bonds are traded via primary dealers

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 before default (our results are robust to alternative definitions). We use all client-to-dealer transactions during the year before 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 before 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.

We now show that investors are likely to sell defaulted bonds to the bond's primary dealer, that is, they trade through dealers who have handled the bond before default. We start with a simple exercise illustrating the intermediation of defaulted bonds by primary dealers around the default event.[12] To do this, we closely track customer-to-dealer trades

[12] 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 with less access to prime brokers who cater to large institutions (Glode and Opp, 2016) need to locate specialized dealers within the dealer network capable of intermediating the distressed securities.

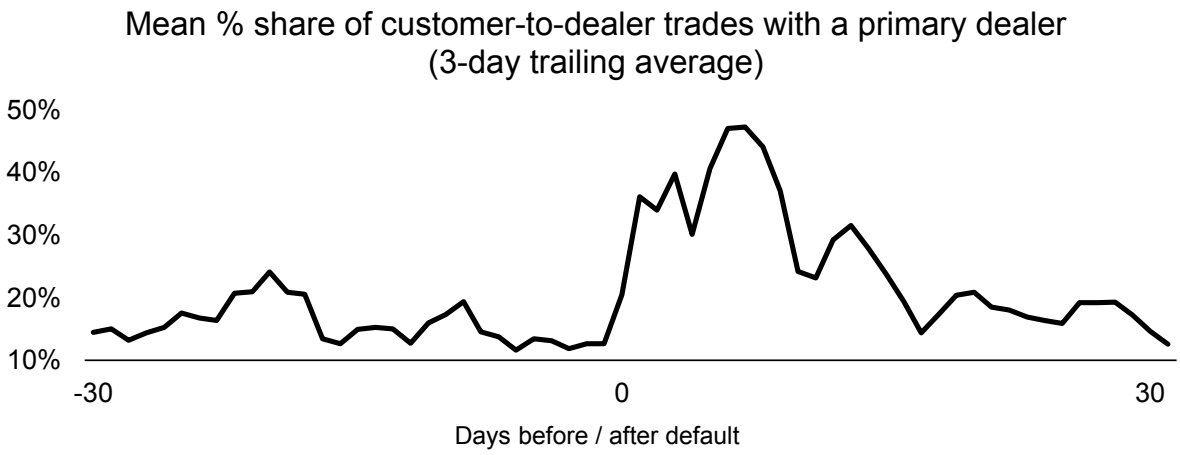


Figure 1: Share of trades with primary dealers as a percentage of the total number of customer-to-dealer trades, 3-day trailing average.

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 1 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, and gradually declines to pre-default levels over the following weeks, consistent with the overall spike in trading activity. Overall, Figure 1 documents a shift in the intermediation towards primary dealers when a bond defaults.

Table 2 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 before 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 2 shows that primary dealers almost double their market share in post-default bond trading,

Table 2: **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 buying bond i 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 before 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 value				# observations	
	Pre-default	Post-default	Post–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			
PrimaryDealer	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

intermediating about 31% of all client-to-dealer trades, compared to less than 17% before default with the net difference being statistically significant at the 1%-level.

Table 2 also examines whether the dealers' role as brokers differs 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% before 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. Last, Table 2 shows that the intra-day intermediation chain length, measured by the number of dealers intermediating the bond, increases significantly from about 1.63 dealers before 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

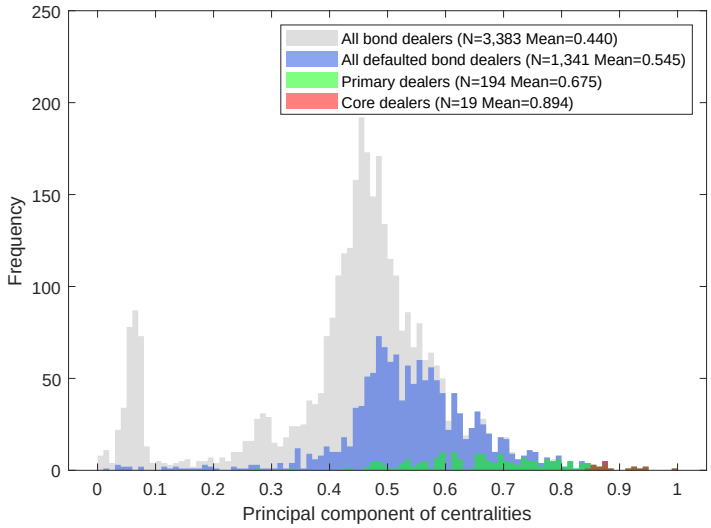


Figure 2: Empirical distributions of dealer centralities within the equal-weighted dealer network. Centrality is scaled on the interval [0,1].

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.

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 (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 2 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.[13]

[13] 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.

The observed uptick in trading around default motivates having a model for investors' selection of dealers when selling defaulted bonds. We 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:

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

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_{ij}^{CD}, is sold to a primary dealer. The sample comprises 547,742 client-to-dealer transactions within the year before default and 30 days after that.[14]

We control for unobserved heterogeneity by including dummies for different default event types, $\mathit{DefaultType}_j$ (Distressed exchange, Risk rating, Chapter 11, Chapter 7 liquidation), as well as year fixed effects and trade size dummies (LargeInstitutional, Retail) and bond characteristics, X_{ij}, including maturity, seasoning, issue size, rating, junk-rated, unrated, enhanced, callable, sinking fund, senior unsecured, senior subordinate, subordinate junior, coupon, CDS availability, covenants.[15] We add the ownership concentration (Herfindahl–Hirschman index, HHI_j) among institutional investors including insurance companies, bond mutual funds, and pension funds in bond j before default, available via eMAXX data. It proxies for a supply shock, given that ownership concentration among investors governed by investment risk-exposure restrictions may force these investors to sell a bond once it defaults. To differentiate the effect of the default event in the propensity to trade with a primary dealer subject to liquidity dry-up, we interact $\mathit{PostDefault}_{ij}$ with HHI_j.[16]

[14] The number of observations is lower than in Table 2, which contains 625,548 transactions over the same period, given that ownership data is missing for some bonds in the eMAXX database.

[15] 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.

[16] Investment mandates and internal and external regulatory constraints restrict the composition of investment portfolios of institutional investors such as insurance companies, bond mutual funds, and pension funds. Except for the spike in volume around the default date, defaulted debt securities may lack liquidity in the secondary 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

Table 3: **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 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%).

	$PrimaryDealer_{ij} \mid Trade_{ij}^{CD}$	
Specification	(1)	(2)
$PostDefault$	0.16**	0.13**
$PostDefault \times$ Pre-default HHI		0.29***
Pre-default HHI	0.06	−0.02
Default type	Yes	Yes
Bond features	Yes	Yes
Seniority FE	Yes	Yes
Trade size FE	Yes	Yes
Year FE	Yes	Yes
# observations	547,742	547,742

Table 3 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 3 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, before the default surprise, the bond is held by institutional investors.

Retail-size trades, defined as trades with less than $100,000 par value, are more likely to

downgrades. 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.

be intermediated by primary dealers 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 statistically 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 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 patterns in the intermediation of defaulted corporate bonds. Every bond in good standing is intermediate by multiple dealers. After the default, the non-primary dealers cut back their intermediation of defaulted bonds. The primary dealer is the predominant intermediary once the bond defaults.

2 Recovery Rates and Dealer Intermediation

Having identified the prevalence of trading defaulted bonds via primary dealers in Section 1.2, we now examine whether the intermediation by primary dealers is associated with lower or higher post-default recoveries for investors.[17] We show that recovery rates are higher when intermediated by primary dealers, controlling for factors outside of the dealers' realm. Recovery rates differ not only across bonds and dealers but also across investors in the same bond compared to the total recovery.

[17] 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. 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.

2.1 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 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:

$$RR_{ij} = \frac{price_{ij}}{par_j}. \tag{2}$$

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 the relationship between trade-level recovery rates and the explanatory variables established in the recovery rate literature, adding the primary dealer indicator as a determinant:

$$RR_{ij} = \alpha + \beta\, PrimaryDealer_{ij} + \delta'\, X_{ij} + \epsilon_{ij}. \tag{3}$$

The controls X_{ij} in (3) 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 4 reports the regression results for specification (3) 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 with dealer fixed effects (specification 1) is our most stringent specification. It yields an extra recovery of \$2.03 per \$100 invested from transacting with the primary dealer, 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 5% premium obtained by investors who sell via primary dealers.

Table 4: **Trade-based recovery rates.** The binary *PrimaryDealer* variable indicates whether the bond is sold to a primary dealer. The recovery rate *RecoveryRate* is the dependent variable in specifications 1–4. Specification 2 controls for dealer-specific effects. Specifications 3 and 4 control for potential endogeneity and selection bias. 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%).

	Trade-level recovery rate RR_{ij} (% of par)			
Specification	(1)	(2)	(3)	(4)
PrimaryDealer	2.03***	4.52***	6.79***	4.24***
Bond features	Yes	Yes	Yes	Yes
Liquidity features	Yes	Yes	Yes	Yes
Macroeconomic features	Yes	Yes	Yes	Yes
Company features	Yes	Yes	Yes	Yes
Seniority FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Industry distress FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Dealer FE	Yes	No	No	No
Empirical model	OLS	OLS	2SLS	Heckman
R^2	0.6185	0.5959	0.5942	0.5961
# observations	108,536	108,536	108,536	108,536

Specification 2 drops the dealer fixed effects from 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 larger magnitude of \$4.52 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. All results reported in Table 4 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. The results are also 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 before default.

A potential concern with explaining trade-level recovery rates (3) is that common shocks can affect both a bond's recovery after the default and primary dealers' incentives to intermediate this bond. To control for potential endogeneity and selection bias, we use several IV approaches. Appendix B discusses these additional specifications in detail. In specification

3, the pre-default ownership concentration among institutional investors serves as an instrument to proxy for a supply shock that drives trading with primary dealers. We again focus on the effect of transacting with a primary dealer, $PrimaryDealer_{ij}$, on the transaction-specific recovery rate. The 2SLS specification (3) produces an extra recovery of \$6.79 per \$100 par value from transacting with primary dealers, statistically significant at the 1%-level and economically significant and, not surprisingly, 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 4 with the same instrument as in specification 3. In this specification, we control for selection bias by adding to specification 2 the inverse Mills ratio as an additional explanatory variable as per Heckman (1979). Again, the *PrimaryDealer* variable increases recoveries by \$4.24 per \$100 par value, both statistically at the 1%-level and economically significant and close to the OLS estimate.

Overall, the results from specifications 1–4 imply that buyers pay (sellers recover) between \$2 and over \$6 more per each \$100 invested on each transaction when transacting with primary dealers instead of other dealers. The significant positive β coefficients in all specifications suggest that trading with primary dealers positively impacts trade-level recovery rates.

Alternative specifications, primary dealer definition, and robustness. Appendix B also explores how the results are affected when we explicitly account for the shift to primary dealers 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.

To further check the robustness of our findings to alternative primary dealer definitions, we run similar regressions with a firm-level primary dealer characteristic in Table B.3, and an underwriter characteristic in Table B.4 in Appendix B. The results reported in both tables are consistent with Table 4. In addition, we investigate whether the introduction of the Volcker Rule has any determining effects on trading with primary dealers and recovery rates. As the results in Table B.5 in Appendix B demonstrate, recovery rates are lower after the implementation of the Volcker Rule, however, the primary dealer effect remains large.

Table 5: **Summary statistics for bond-level recovery rates.** The total 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 days thereafter.

	Total recovery rate RR_j (% of par)								
Statistic	*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%

2.2 Total recovery in default

The impact of intermediation by the primary dealer(s) at the bond level differs from trade-level recovery rates of individual investors to the extent that dealers add value during the intermediation process thus improving recovery for all investors. The model of dealer intermediation in default in Section 3 will rationalize this difference.

Bond-level recovery. The bond-level recovery can be measured by aggregating across all trades after default. The total recovery rate in bond j, similar to the one used in Jankowitsch, Nagler, and Subrahmanyam (2014), equals:

$$RR_j = \frac{1}{T+1} \sum_{s=t}^{t+T} \left(\frac{1}{|K_{js}|} \sum_{i \in K_{js}} RR_{ij} \right), \tag{4}$$

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 5 reports summary statistics for bond-level recovery rates defined in (4) 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 observed wide variation in recovery rates 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 (Mora, 2015).

Relation between bond-level recovery and primary dealers. 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 intermediated by the primary dealer as

$$PrimaryDealer_j \equiv \frac{1}{I_j + 1} \sum_{i=0}^{I_j} PrimaryDealer_{ij}, \tag{5}$$

where $I_j + 1$ is the number of client-to-dealer trades in bond j.

We set up a specification similar to (3) 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]

$$RR_j = \alpha + \beta\, PrimaryDealer_j + \delta'\, X_j + \epsilon_j, \tag{6}$$

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

Table 6 reports results for the impact of the intermediation by primary dealers on bond-level recovery rates. We first discuss OLS estimates for β. In Specification 1, we use the share of primary dealer participation across all post-default trades. Specification 2 is identical to specification 1 except we do not simultaneously control for dealer characteristics including central dealer (defined as a binary indicator denoting whether a dealer is located

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

Table 6: **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 total 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 1-2, and 3-4, 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%).

	Total recovery rate RR_j (% of par)			
Specification	(1)	(2)	(3)	(4)
PrimaryDealer	6.08**	6.79**	4.67*	4.03*
Dealer features	Yes	No	Yes	No
Default type	Yes	No	Yes	No
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
Empirical model	OLS	OLS	Bartik	Bartik
R^2	0.6312	0.6303	0.6297	0.6273
# observations	2,093	2,093	1,275	1,275

in the network's core), dealer size, and dealer inventory. The estimate of β is economically large and statistically significant at 5%-level. OLS regression specifications 1/2 suggest that recovery rates for a given bond are \$6.08/\$6.79 per \$100 invested higher when transacting with primary dealers instead of non-primary dealers.

To alleviate concerns about the endogeneity of (5), 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 2.1. 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 defaulted bond:

$$\widehat{PrimaryDealer}_j = \frac{1}{I_j + 1} \sum_{i=0}^{I_j} \widehat{\Pr}(PrimaryDealer_{ij}). \tag{7}$$

Specifications 3 and 4 are identical to specifications 1 and 2, 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 3 and 4 because the eMAXX data is missing in some cases. The IV estimates are smaller than the OLS estimate, at values of \$4.67/\$4.03 per \$100 par value. Still, the estimates are more than twice as large as the estimate of the trade-specific recovery rate from column 1 of Table 4. 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 dealer size, inventory, and centrality.

In summary, trading with primary dealers yields a trade-level price premium of \$2.03 to \$6.79 per \$100 par value and a bond-level premium of \$4.03 to \$6.79 per \$100 par value. A natural question is how primary dealers generate such large recovery gains for investors.

3 Model of Dealer Intermediation in Default

In this section, we develop a stylized model of distressed bond intermediation by primary dealers consistent with our findings that trading defaulted bonds via primary dealers leads to a large bond-level recovery (and larger bond-level than trade-level recoveries). To fix ideas, let primary dealers be better at searching and matching distressed bond buyers and sellers than other dealers (Duffie, Garleanu, and Pedersen, 2005; Hugonnier, Lester, and Weill, 2019; Sambalaibat, 2022). In addition, primary dealers are better than other dealers at allocating distressed bonds to these investors (Feldhütter, Hotchkiss, and Karakaş, 2016; Glode and Opp, 2019; Chaderina and Glode, 2023). Trading with a primary dealer results then in better allocation efficiency potentially leading to higher total recovery.

3.1 Setup and main results

A single generic distressed bond is sequentially traded in the model bilaterally via trades $i = 1, ..., I$. With probability p, a transaction i is intermediated by the primary dealer, and with probability $1 - p$ it is intermediated by a non-primary dealer. The type of dealer intermediating transaction i is captured by a trade indicator $D_i \in \{0, 1\}$, which is independent across transactions and equal to one for primary dealers and zero for non-primary dealers, so that $\mathbb{E}[D_i] = p$ and $\text{Var}(D_i) = p(1 - p)$. We assume a linear pricing rule for the recovery

rate, RR_i,

$$RR_i = a + bD_i + c\pi_i + \eta_i, \tag{8}$$

where a is a constant and η_i is a zero-mean pricing error independent across transactions and uncorrelated with D_i for all i. The second term in relation (8) with a constant b captures the *direct* price effect from the intermediation by the primary dealers. Positive b implies direct price improvement. Primary dealers may have lower search and matching costs they may pass to clients via price improvement (Duffie, Garleanu, and Pedersen, 2005; Hugonnier, Lester, and Weill, 2019; Sambalaibat, 2022). Another channel is that primary dealers may switch to riskless principal trades after default and thus may be 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). Another possible channel is that primary dealers may have lower inventory costs and pass some savings to clients as price improvement (Bessembinder, Jacobsen, Maxwell, and Venkataraman, 2018). Conversely, negative b implies direct price disimprovement. This may be because primary dealers charge higher markups.

The recovery rate RR_i also depends on the belief, π_i, about the success of the distress resolution and/or the size of recoveries that will accrue bondholders with the initial belief equal to π_0. Here we have in mind that the total recovered amount will be larger thus increasing the bondholders' fixed stake, or the recovered amount will stay the same but bondholders will be able to negotiate a larger stake in the recovered funds, or both. Constant $c > 0$ in (8) is the elasticity of the recovery rate to π_i. Beliefs evolve with each transaction according to

$$\pi_i = \pi_{i-1} + \alpha D_i - \delta\pi_{i-1}(1 - D_i) + \rho\pi_{i-1}D_i + \varepsilon_i, \tag{9}$$

where ε_i is a random zero-mean belief shock independent across transactions and uncorrelated with D_i for all i.

To motivate the belief dynamics, consider two types of investors in the market for distressed corporate bonds: specialized vulture investors (such as specialized vulture funds and other informed expert investors) and speculators. Specialized vulture investors accumulate distressed bonds to increase their bargaining position in negotiating the bondholders' stake in the recovered value and to influence the debtor firm restructuring by participating in firm-level activities aimed at improving the value of debt claims (Wruck, 1990; Hotchkiss and Mooradian, 1997; Jiang, Li, and Wang, 2012; Ivashina, Iverson, and Smith, 2016). Hotchkiss and Mooradian (1997) document that the post-default restructuring operating performance relative to the pre-default level is often greater when vulture investors gain control of the

distressed firm. The coefficient $\alpha \geq 0$ captures the incremental belief improvement about the outcome of the debtor firm restructuring. Alternatively, it can be viewed as a premium in bond prices due to the value of creditor control as in Feldhütter, Hotchkiss, and Karakaş (2016), since trading with primary dealers increases creditor control.

Higher trade-level recovery rates RR_i provide a positive signal that boosts confidence in the ability to recover more on the distressed debt, modeled via stronger persistence in beliefs captured by $\rho\pi_{i-1}D_i$ in the belief evolution (9), with $\rho \in [0,1]$. This increased confidence leads to more favorable terms in future transactions, creating a positive feedback loop that amplifies the initial positive impact. Contrary to vulture investors, speculators buy the dip and seek to profit from potential future price appreciations by free-riding on the vulture investors' actions to improve bondholders' recovery. The reallocation of bonds from vulture investors to speculators diminishes the former investors' ability to improve bondholders' recovery thus deteriorating beliefs about it captured via $-\delta\pi_{i-1}(1-D_i)$ in the belief evolution (9), with $\delta \in (0,1]$. This reduced confidence in bondholders' recovery leads to less favorable terms in future transactions. Finally, the length of intermediation chains is set through investors' outside option of not trading when the belief falls below some threshold $\underline{RR}$, which generates chain lengths that depend on primary dealer intermediation.[19]

We start by calculating the average belief, $A_I \equiv \mathbb{E}[\pi_i]$, indexed by the number of trades I (Appendix C provides additional details). Taking an expectation of expression (9) we obtain the recursion $A_I = \alpha p + \kappa A_{I-1}$ with the growth rate of

$$\kappa \equiv 1 + \rho p - \delta(1-p) \in (0,1). \tag{10}$$

The expression for κ reflects that relative to the prior beliefs captured by 1, each transaction improves beliefs about the recovery at the average rate of ρp and deteriorates beliefs about the recovery at the average rate of $\delta(1-p)$. For the growth rate κ to be in the interval $(0,1)$, we need the average rate of value improvement, ρp, to be less than the average rate of value destruction, $\delta(1-p)$, resulting in the following condition

$$\frac{p}{1-p} < \frac{\delta}{\rho}.$$

[19] Glode and Opp (2016) show that longer intermediation chains weaken traders' incentives to screen counterparties thus reducing the adverse selection and increasing trade efficiency. Asymmetric information about the residual value of the bondholders who are subordinated claim holders may also rise after the default (Glode and Opp, 2019).

We assume that beliefs improve at a higher rate than they deteriorate, $\delta < \rho$, implying from the inequality (10) that $p < 1 - p$.

Solving the recursion with the initial condition $A_0 = \pi_0$ yields

$$A_I = \alpha p \frac{1 - \kappa^I}{1 - \kappa} + \kappa^I \pi_0 = A_\infty - \kappa^I (A_\infty - A_0). \tag{11}$$

where the large sample, $I \to \infty$, expected beliefs are equal to

$$A_\infty = \frac{\alpha p}{1 - \kappa}. \tag{12}$$

The expression for A_∞ reflects that with the large number of transactions the expected beliefs are equal to the average trade-level belief improvement, αp, multiplied by the value of the perpetuity growing at the rate κ.

Following the empirical specification (3), the trade-level coefficient from regressing the recovery rate on the primary dealer indicator, β^{TL}, can be calculated as

$$\beta^{\text{TL}} = \frac{\text{Cov}(D_i, RR_i)}{\text{Var}(D_i)} = b + c \frac{\text{Cov}(D_i, \pi_i)}{\text{Var}(D_i)}. \tag{13}$$

In Appendix C we establish the following result.

RESULT 1: *The trade-level coefficient from regressing the recovery rate on the primary dealer indicator is equal to*

$$\beta^{\text{TL}} = b + c(\alpha + (\rho - \delta) A_{I-1}). \tag{14}$$

The expression for β^{TL} has a simple economic intuition. The direct price improvement, the second term in the price relation (8), is the per-transaction value created by primary dealers and, therefore, it contributes a constant b to β^{TL}. Trading with primary dealers improves the realized trade-level recovery rate by $c\alpha$. Trading with primary dealers also strengthens the beliefs about the recovery, $(\rho - \delta) A_{I-1}$, instead of them deteriorating as $-\delta A_{I-1}$ when primary dealers are not in the market. Primary dealers, therefore, boost market confidence about the recovery and stabilize prices.

We now follow expression (4) to construct the aggregate recovery rate for the transaction chain of length $I + 1$ in the model

$$\overline{RR} \equiv \frac{1}{I+1} \sum_{i=1}^{I+1} RR_i, \tag{15}$$

and expression (5) to construct the aggregate primary dealer index in the model

$$\overline{D} \equiv \frac{1}{I+1}\sum_{i=1}^{I+1} D_i. \tag{16}$$

The bond-level regression coefficient of the aggregate recovery rate on the aggregate primary dealer index is then equal to

$$\beta^{\text{BL}} = b + c\frac{\text{Cov}(\overline{RR}, \overline{D})}{\text{Var}(\overline{D})} = b + \frac{c}{I+1}\frac{\text{Cov}(\sum_{i=1}^{I+1} RR_i, \sum_{i=1}^{I+1} D_i)}{p(1-p)}, \tag{17}$$

where $\text{Var}(\overline{D}) = p(1-p)/(I+1)$. As shown in Appendix C, solving for a convenient closed-form expression for β^{BL} is possible only in the large I limit, $I \to \infty$, leading to the following result.

RESULT 2: *The bond-level coefficient from regressing the aggregate recovery rate on the aggregate primary dealer indicator is equal in the large I limit to*

$$\beta^{\text{BL}}_{I\to\infty} = b + \frac{c}{1-\kappa}(\alpha + (\rho - \delta)A_\infty). \tag{18}$$

It is clear from (18) that because $\kappa < 1$, $\beta^{\text{BL}}_{I\to\infty}$ is greater than $\beta^{\text{TL}}_{I\to\infty}$ given by

$$\beta^{\text{TL}}_{I\to\infty} = b + c(\alpha + (\rho - \delta)A_\infty). \tag{19}$$

This result is consistent with the empirical findings in Section 2. It is also clear that primary dealers must generate value for investors beyond passing efficiency cost savings into prices, e.g. direct price improvement in the model. The direct price improvement is transitory and thus does not depend on the number of trades and contributes the same constant b to both $\beta^{\text{TL}}_{I\to\infty}$ and $\beta^{\text{BL}}_{I\to\infty}$. Primary dealers affecting the recovery belief component of prices is key for $\beta^{\text{BL}}_{I\to\infty}$ to be greater than $\beta^{\text{TL}}_{I\to\infty}$. Beliefs at any position in the transaction chain aggregate all changes due to past transactions thus making recovery rates correlated with past primary dealer indicators. Consequently, the covariance between the aggregate recovery rate and the aggregate primary dealer index is greater than the sum of the covariances between the trade-level recovery rates and primary dealer indices since the latter does not account for the correlation between individual transactions.

Primary dealer intermediation generates a positive feedback loop in the trade-level recovery rates. This is because $\text{Cov}(RR_i, D_{i-l}) = \kappa^l \text{Cov}(RR_{i-l}, D_{i-l})$ is positive resulting in

past trades affecting future trade-level recovery rates by boosting confidence about the bondholders' recovery, the channel we can verify in the data. We guide the empirical analysis by quantifying the feedback loop effect in the model as the coefficient from regressing the trade-level recovery rate on the lagged aggregate primary dealer index

$$\gamma^{\text{FE}} = \frac{\text{Cov}(RR_{I+1}, \frac{1}{I}\sum_{i=1}^{I} D_i)}{\text{Var}(\frac{1}{I}\sum_{i=1}^{I} D_i)} = \frac{\text{Cov}(RR_{I+1}, \sum_{i=1}^{I} D_i)}{p(1-p)}. \tag{20}$$

γ^{FE} captures the trade-level recovery rate boost from all *past* transactions with the primary dealer, whereas β^{TL} is the contemporaneous effect on the recovery rate from transacting with the primary dealer. It is straightforward to verify that in the large I limit we have

$$\gamma^{\text{FE}}_{I\to\infty} = \beta^{\text{BL}}_{I\to\infty} - \beta^{\text{TL}}_{I\to\infty} = c\frac{\kappa}{1-\kappa}(\alpha + (\rho - \delta)A_\infty). \tag{21}$$

This relation implies the feedback effect is a wedge between bond-level and trade-level regression coefficients in recovery rate regressions.

In the next subsections, we check for supporting evidence in the data on the persistence parameter ρ and the feedback loop effect and price-stabilizing role of primary dealers.

3.2 Role of primary dealer early in bondholders' recovery process

While the coefficients are larger for primary dealers in the aggregate regressions (compare Table 4 with Table 6), we have not yet tested why this is the case. To establish supporting evidence for $\rho > 0$ in (9), we add and interact a dummy variable to the trade-level recovery rate regression that indicates whether a trade in a defaulted bond takes place within 5 days after default with the primary dealer characteristic, denoted $(DaysSinceDefault < 5)$:

$$RR_{ij} = \alpha + \beta\, PrimaryDealer_{ij} + \gamma\, PrimaryDealer_{ij} \times (DaysSinceDefault < 5) + \\ + \delta'\, X_{ij} + \epsilon_{ij}. \tag{22}$$

We use the same controls X_{ij} as in specification (3) and cluster standard errors by bond issue and time. A total of 107,067 post-default observations are included in the recovery rate specification (22).

Under our feedback loop hypothesis, we expect the coefficient γ to be positive. In this case, the effect of primary dealers on recovery rates is largest immediately after default. An

Table 7: **Primary dealer role early in the recovery process.** The binary *PrimaryDealer* variable indicates whether the bond is sold to a primary dealer. The recovery rate *RecoveryRate* is the dependent variable in specifications 1–4. Specification 2 controls for dealer-specific effects. Specifications 3 and 4 control for potential endogeneity and selection bias. A total of 107,067 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%).

	Trade-level recovery rate RR_{ij} (% of par)			
Specification	(1)	(2)	(3)	(4)
PrimaryDealer	0.73	2.76***	5.14**	2.55***
PrimaryDealer × (*DaysSinceDefault* < 5)	3.21**	3.74**	3.25*	3.70**
(*DaysSinceDefault* < 5)	−2.58**	−2.89**	−2.81**	−2.87**
Bond features	Yes	Yes	Yes	Yes
Liquidity features	Yes	Yes	Yes	Yes
Macroeconomic features	Yes	Yes	Yes	Yes
Company features	Yes	Yes	Yes	Yes
Seniority FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Industry distress FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Dealer FE	Yes	No	No	No
Empirical model	OLS	OLS	2SLS	Heckman
R^2	0.6207	0.5991	0.5970	0.5992
# observations	107,067	107,067	107,067	107,067

alternative is the informed trading hypothesis (Kyle, 1985; Babus and Kondor, 2018). In this case, we would expect that informed bond traders who trade through primary dealers push up prices and do so more over time, as the information that they accumulate positions slowly trickles into beliefs about bondholders' recovery. The effect of primary dealers on recovery rates would then magnify over time and would be smaller immediately after default compared to later points in time. The coefficient γ would then be negative.

The results in Table 7 demonstrate that the effect of primary dealers on recovery rates magnifies immediately after default (in this case 5 days after default) as compared to later points in time during the 30 days after default (the combined coefficients of $(DaysSinceDefault < 5)$ and $PrimaryDealer{*}(DaysSinceDefault < 5)$ increase the recovery rate. The coefficient on $PrimaryDealer$ is smaller than the one on $PrimaryDealer \times (DaysSinceDefault < 5)$ in column 1. This suggests the primary dealer increases trade-level recovery by more, equal

to \$3.94 = \$0.73+\$3.21 (per \$100 invested) in specification 1, immediately after default than later during the recovery process, equal to \$0.73 in specification 1. In specification 2, the early effect is \$6.50 = \$2.76+\$3.74 while the late effect is significant at \$2.76. In specifications 3 and 4, both effects are positive at \$8.39 (\$6.35) early and \$5.14 (\$2.55) late.

These results support the notion that the magnitude of trading with a primary dealer differs depending on the timing as well as evidence of the increasing market-wide confidence over time after default.

3.3 Feedback effect from trading with primary dealers

To test the model's feedback effect more directly, in the spirit of the model-implied lagged aggregate primary dealer index used in relation (20), $\frac{1}{I}\sum_{i=1}^{I} D_i$, we now introduce such index in the data as

$$\overline{PrimaryDealer}_{i-1j} = \frac{1}{i}\sum_{l=1}^{i} PrimaryDealer_{i-lj}, \tag{23}$$

where i indicates the transaction and j indexes the defaulted bond. We then add $\overline{PrimaryDealer}_{i-1j}$ to specification (3) resulting in

$$RR_{ij} = \alpha + \gamma\, \overline{PrimaryDealer}_{i-1j} + \beta\, PrimaryDealer_{ij} + \delta'\, X_{ij} + \epsilon_{ij}. \tag{24}$$

We use the same controls X_{ij} as in specification (3) and cluster standard errors by bond issue and time. A total of 107,067 post-default observations are included in the recovery rate specification (24).

Table 8 reports the regression results for specification (24) estimated from trade-level recovery rates. We focus on the feedback effect from past trades with the primary dealer, $\overline{PrimaryDealer}_{i-1j}$, and the effect of transacting with a primary dealer, $PrimaryDealer_{ij}$, on the trade-specific recovery rate. The standard OLS specification 1 with dealer fixed effects is our most stringent specification. In agreement with the model, past trading with the primary dealer yields (via a feedback loop) an additional \$6 per \$100 invested, statistically (at the 1%-level) and economically significant. This is three times the recovery rate improvement estimated from the contemporaneous transaction with the primary dealer in Table 4. Given that the mean bond-level recovery rate in our sample is \$38.8 per \$100 invested, the feedback effect implies a sizeable recovery premium obtained by investors who transact defaulted bonds repeatedly intermediated by primary dealers. As the regression coefficient on $PrimaryDealer_{ij}$ is close to zero, it shows that trading with the primary dealer yields little

Table 8: **Positive feedback effect.** The binary *PrimaryDealer* variable indicates whether the bond is sold to a primary dealer. $\overline{PrimaryDealer}$ is a lagged indicator variable of whether the bond is sold to a primary dealer. The recovery rate *RecoveryRate* is the dependent variable in specifications 1–4. Specification 2 controls for dealer-specific effects. Specifications 3 and 4 control for potential endogeneity and selection bias. A total of 107,067 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%).

	Trade-level recovery rate RR_{ij} (% of par)			
Specification	(1)	(2)	(3)	(4)
$\overline{PrimaryDealer}$	6.01***	6.72***	7.29***	7.04***
PrimaryDealer	0.00	1.92**	3.17*	1.97**
Bond features	Yes	Yes	Yes	Yes
Liquidity features	Yes	Yes	Yes	Yes
Macroeconomic features	Yes	Yes	Yes	Yes
Company features	Yes	Yes	Yes	Yes
Seniority FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Industry distress FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Dealer FE	Yes	No	No	No
Empirical model	OLS	OLS	2SLS	Heckman
R^2	0.6260	0.6047	0.6047	0.6047
# observations	107,067	107,067	107,067	107,067

direct improvement. In the context of the model, this implies that constant b capturing the direct price effect from the intermediation by the primary dealers is negative, i.e., primary dealers tend to charge higher markups for instance, and of the same order of magnitude as the second term in the expression (14) for β^{TL}.

The coefficient on $\overline{PrimaryDealer}_{i-1j}$ in specification 2 is equal to 6.72, statistically significant at the 1%-level. The magnitude of the coefficient agrees well with the bond-level coefficients in Table 6. The *PrimaryDealer* coefficient is now positive and represents \$1.92 per \$100 invested, statistically (at the 5%-level) and economically significant. It confirms that a large part of the improvements in recovery rates coming from the intermediation by primary dealers are due to them "boosting beliefs" about bondholders' recovery outcome thus creating a positive feedback loop from past transactions into the contemporaneous recovery rates. It further underscores the ability of primary dealers to reallocate defaulted/distressed

bonds to distressed bond investors who influence the bondholders' recovery. The results in the remaining specifications are similar to specification 2.

Overall, these results suggest that past primary dealer intermediation early in the recovery process matters more for boosting recovery values—the feedback loop effect—than the presence of a primary dealer in the current transaction, presumably due to improved search and other benefits.

3.4 Price-stabilizing role of primary dealers

The defaulted-bond setting is special in that bond valuations are (endogenously) determined by who holds the bonds during the restructuring process. The dealers can boost market confidence by counterbalancing selling pressure and locating high-valuation buyers such as specialized vulture investors that can reap higher recoveries in post-default negotiations. To validate that primary dealers counterbalance the negative price impact from selling pressure during default (and in fact 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.[20]

We compute 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

[20] 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.

client-to-dealer transactions from 31 to 40 days after default:

$$PriceRebound_{ij} = \frac{1}{10}\sum_{t=31}^{40}\left(\frac{1}{|K_{jt}|}\sum_{k\in K_{js}} RR_{kj}\right) - RR_{ij}, \tag{25}$$

where K_{jt} is the number of trades in bond j on day t, starting 31 days after default and 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:

$$PriceRebound_{ij} = \alpha + \beta\, PrimaryDealer_{ij} + \delta'\, X_{ij} + \epsilon_{ij}, \tag{26}$$

The control variables are similar to those used in (3). Here, a total of 106,992 post-default client-to-dealer trades are considered. We expect more efficient prices and hence less price rebound due to the primary dealer's expertise. Given that bonds sold to primary dealers immediately following a default event achieve higher recoveries, the subsequent price reversal should be less pronounced for these transactions.

Table 9 reports our results for four variants of specifications (26). The two columns to the left use the primary dealer indicator as an explanatory variable, with (specification 1) and without (specification 2) dealer fixed effects. Specification 3 considers the instrumented primary dealer indicator, and specification 4 follows the self-selection correction approach of Heckman (1979) with the instrument created as in Table 4.

The regression coefficients range between -\$0.81 and -\$5.62 and are economically and statistically significant, suggesting that post-default prices rebound less when intermediated by primary dealers. A natural interpretation of these findings is that primary dealer prices are *more informationally efficient* and less driven by fire sale discounts. As all four columns show, selling to primary dealers immediately after default is tantamount to counterbalancing temporary price pressure, given that the following price rebound is less pronounced for those trades routed via primary dealers. These findings also alleviate concerns that the estimates in Tables 7 and 8 may be driven by slow-moving capital, fire sale discounts, or temporary price pressures.

Overall, the results show that trading with a primary dealer leads to higher and more sta-

Table 9: **Post-default price rebound.** The price appreciation *PriceRebound* is the dependent variable. 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%).

	$PriceRebound_{ij}$			
Specification	(1)	(2)	(3)	(4)
PrimaryDealer	−0.81*	−3.19***	−5.62***	−2.24**
Bond features	Yes	Yes	Yes	Yes
Liquidity features	Yes	Yes	Yes	Yes
Macroeconomic features	Yes	Yes	Yes	Yes
Company features	Yes	Yes	Yes	Yes
Seniority FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Industry distress FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Dealer FE	Yes	No	No	No
Empirical model	OLS	OLS	2SLS	Heckman
R^2	0.4956	0.4595	0.4594	0.4663
# observations	106,992	106,992	106,992	106,992

ble recovery prices after default vis-à-vis prices observed once the initial default surprise has vanished. These findings suggest that primary dealers boost confidence about the recovery outcome rendering prices permanently higher. The question of whether informational differences and beliefs drive the primary dealer premium and, accordingly, how primary dealers reallocate defaulted bonds remains and we explore it in Section 4.

4 Dealers' Role in Trading Defaulted Bonds

This section documents how primary dealers reallocate defaulted bonds. In the model, the length of intermediation chains is set through investors' outside option $\underline{RR}$ which generates chain lengths that depend on how primary dealers affect market confidence about recovery. We therefore investigate the shift in dealers' trading networks and the length of intermediation chains which is related to information asymmetries (Glode and Opp, 2016; Glode and Opp, 2019). We also document dealers' role as principal traders as opposed to brokers, whether dealers are willing to place defaulted bonds in their inventories or prearrange

trades, and how the extensive margin of intra-day trading, i.e., probability of matching with the counterparty within a day is affected by default (Bessembinder, Jacobsen, Maxwell, and Venkataraman, 2018; Bao, O'Hara, and Zhou, 2018; Goldberg and Nozawa, 2021).

4.1 Shift in dealers' trading network

We first create a corporate bond inter-dealer network based on dealer-to-dealer transactions reported to TRACE, following the approach in Li and Schürhoff (2019). Figure 3 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. Figure 3 shows that 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.

Table A.1 in the Appendix 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.[21]

4.2 Intermediation chains in defaulted bonds

Glode and Opp (2016) show that intermediation chains are related to information asymmetries. Their theory suggests that if primary dealers intermediate trades where asymmetric information is larger (consistent with the findings in the prior section), chains should get longer. We therefore examine whether intermediation chains change for bonds affected by default. Specifically, we analyze the length of intra-day round-trip intermediation chains

[21] 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.

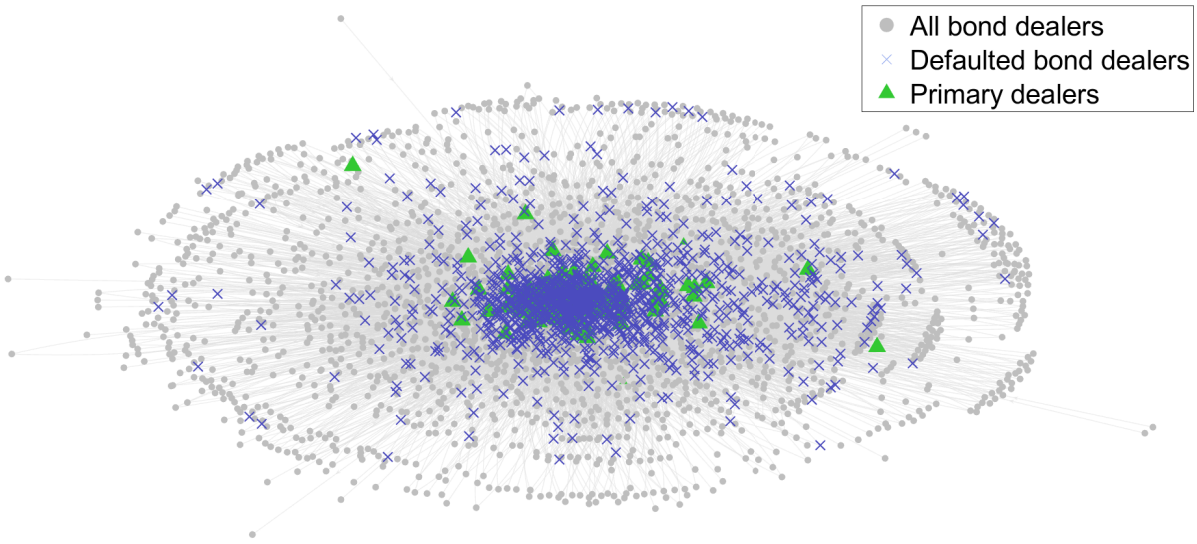


Figure 3: **Dealer network before and after default.** The figure illustrates the defaulted-bond dealer network, representing 44,065,910 inter-dealer transactions. Nodes represent the 3,383 bond dealers and links indicate trade relationships between two dealers via bond transactions reported to TRACE. 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.

and how they relate to primary and non-primary dealers' ability to successfully 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.[22] 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.[23] 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

[22] 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.

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

Table 10: **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***
Dealer features	No	No	Yes	Yes	Yes
Default type	No	Yes	Yes	Yes	Yes
Bond features	No	Yes	Yes	Yes	Yes
Seniority FE	No	Yes	Yes	Yes	Yes
Trade size FE	Yes	Yes	Yes	Yes	Yes
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

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:

$$log(N_{ij}) \mid RoundTrip_{ij}^{C(N)DC} = \alpha_0 + \alpha_1\, PostDefault_{ij} \times PrimaryDealer_{ij} + \\ + \alpha_2\, PostDefault_{ij} + \alpha_3\, PrimaryDealer_{ij} + \beta'\, X_{ij} + \epsilon_{ij}, \quad (27)$$

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 (27), 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 10, reports our results for specification (27) 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 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 10, and then add dealer size, centrality, inventory, and the broker role dummy, column 3 of Table 10, 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 10 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

Table 11: **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***
Dealer features	No	No	Yes	Yes	Yes
Default type	No	Yes	Yes	Yes	Yes
Bond features	No	Yes	Yes	Yes	Yes
Seniority FE	No	Yes	Yes	Yes	Yes
Trade size FE	Yes	Yes	Yes	Yes	Yes
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 initiate shorter intermediation chains.

4.3 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.[24]

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-

[24] 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.

dealer trades during the year before a bond's default event until 30 days thereafter:

$$\Pr(BrokerRole_{ij} \mid Trade_{ij}^{CD}) = \Phi(\alpha_0 + \alpha_1\, PostDefault_{ij} \times PrimaryDealer_{ij} + \\ + \alpha_2\, PostDefault_{ij} + \alpha_3\, PrimaryDealer_{ij} + \beta'\, X_{ij}), \quad (28)$$

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

Table 11 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 risk their own capital for intermediating defaulted bonds for which they had handled most of the order flow before 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.

4.4 Intra-day matching

We estimate whether default events impact 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

Table 12: **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
Dealer features	No	No	Yes	Yes	Yes
Default type	No	Yes	Yes	Yes	Yes
Bond features	No	Yes	Yes	Yes	Yes
Seniority FE	No	Yes	Yes	Yes	Yes
Trade size FE	Yes	Yes	Yes	Yes	Yes
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

a consecutive dealer-to-client trade (*CDC* round-trip) or dealer-to-dealer trade (*CDD* trade chain) on the same day ($IntraDayMatch_{ij} = 1$), or whether the dealer keeps the bond in inventory overnight ($IntraDayMatch_{ij} = 0$):

$$\Pr(IntraDayMatch_{ij} \mid Trade_{ij}^{CD}) = \Phi(\alpha_0 + \alpha_1\, PostDefault_{ij} \times PrimaryDealer_{ij} + \\ + \alpha_2\, PostDefault_{ij} + \alpha_3\, PrimaryDealer_{ij} + \beta'\, X_{ij}). \quad (29)$$

Variable definitions are similar to those used in specification (27). Additionally, we include an interaction term between $PostDefault_{ij}$ and $PrimaryDealer_{ij}$ in the baseline specification. We adjust standard errors for heteroskedasticity and cluster by bond issue and time.

Table 12 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 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.

4.5 Inventory risk taking

We now explore dealers' role in facilitating defaulted bonds' transactions by providing inventory capacity, and potentially conducting proprietary trading in defaulted bonds. In subsection 4.4 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 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,

Table 13: **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 before default.

	Dealer inventory							
Statistic	*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%
Post–Pre		0.9%***						

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. Specifically, 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 13 reports summary statistics of dealer inventories. Here, the reference date is one year before 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 days 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% 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 before default further demonstrates, dealers absorb selling pressure even when the bond has not yet defaulted.

4.6 Discussion and Outlook

Our findings highlight the critical role of dealer intermediation in stabilizing distressed bond markets and mitigating credit risk for bondholders, given that recovery rates in default are a

significant determinant of credit risk. While several influential papers have examined the role of liquidity in corporate bond pricing—focusing on how liquidity risk impacts bond returns (Longstaff, Mithal, and Neis, 2005; Chen, Lesmond, and Wei, 2007; Lin, Wang, and Wu, 2011; Bongaerts, Jong, and Driessen, 2017)—our paper centers on liquidity specifically in the context of defaulted bonds. We demonstrate that the primary dealers' supply of liquidity significantly influences bond prices during default.

Recent literature has also explored the risk factors pricing the cross-section of expected excess returns in corporate bonds (Dickerson, Mueller, and Robotti, 2023; Baltussen, Muskens, and Verwijmeren, 2024; Dick-Nielsen, Feldhütter, Pedersen, and Stolborg, 2024; Dickerson and Nozawa, 2024). Several of these studies explore the complications arising from defaulted bonds and their impact on pricing models. Our findings suggest that the relationship between liquidity and credit risk is even more intertwined than previously documented. This raises a question for future research: how does the concentration of trading defaulted bonds via primary dealers affect the pricing of liquidity- and credit-related risk factors. Examining this could provide further insights into the endogenous dynamics of credit markets and the mechanisms by which intermediation affects risk pricing.

5 Conclusion

While there exists extensive literature on the intermediation of corporate bonds in good standing, little is known about the intermediation of defaulted corporate bonds. Our empirical analysis shows that intermediation patterns undergo significant changes after a bond's default. As trading spikes upon default, the bond's primary dealers, who are the most active before default, intermediate up to 50% of the order flow in defaulted bonds. Intermediation by primary dealers leads to better market outcomes. When trades are routed via primary dealers, trade-level recovery rates, measured as trade-level prices as a fraction of par value, increase by over \$2 per each \$100 par value. Bond-level recovery rates, measured as the average transaction price over par value, increase even more, by up to \$7 per each \$100 par value.

These findings cannot be fully explained by theories suggesting that primary dealers only create value for clients directly via lower search, matching, inventory, and transaction costs. Direct price improvements are transitory and lead to equal trade- and bond-level recovery rates. Motivated by the empirical literature on the role of vulture investors in improving distressed debt values (Wruck, 1990; Hotchkiss and Mooradian, 1997; Jiang, Li, and Wang,

2012), we develop a simple model of intermediation of distressed debt linking trade-level prices to debtor-level restructuring activities. The informational component of distressed bonds' prices loads on the belief about the recovery outcome, and primary dealers affect the recovery by allocating distressed bonds to informed higher-recovery vulture investors. Trading with primary dealers is therefore a positive signal about the bond's fundamentals, and the bond-level recovery rate captures the aggregate belief, which is greater than its trade-level component.

Consistent with the model, we find that primary dealer intermediation early in the recovery process—by boosting beliefs about recovery values and creating a feedback loop where prices in earlier transactions influence subsequent ones—has a greater impact than the presence of a primary dealer in later transactions, where any additional value stems from improved search and other transitory benefits. We also observe that the post-default price rebound is less pronounced for trades routed through primary dealers, indicating that trading via a primary dealer results in higher and more stable recovery values.

Our paper offers a novel perspective on the determinants of defaulted bond recovery values, which are usually explained by fundamental drivers such as bond and firm characteristics, macroeconomic conditions (Acharya, Bharath, and Srinivasan, 2007; Bruche and Gonzalez-Aguado, 2010; Nazemi and Fabozzi, 2018), and observable market dynamics of defaulted debt securities (Altman, Brady, Resti, and Sironi, 2005; Jankowitsch, Nagler, and Subrahmanyam, 2014). We show the important role of the dealer sector by linking the intermediation of defaulted bonds to debtor-level restructuring outcomes.

References

Acharya, V. V., S. T. Bharath, and A. Srinivasan (2007). "Does industry-wide distress affect defaulted firms? Evidence from creditor recoveries". In: *Journal of Financial Economics* 85.3, pp. 787–821.

Altman, E. I., B. Brady, A. Resti, and A. Sironi (2005). "The link between default and recovery rates: Theory, empirical evidence, and implications". In: *Journal of Business* 78.6, pp. 2203–2228.

Altman, E. I. and V. M. Kishore (1996). "Almost everything you wanted to know about recoveries on defaulted bonds". In: *Financial Analysts Journal* 52.6, pp. 57–64.

Babus, Ana and Péter Kondor (2018). "Trading and Information Diffusion in Over-the-Counter Markets". In: *Econometrica* 86.5, pp. 1727–1769.

Baltussen, Guido, Frederik Muskens, and Patrick Verwijmeren (2024). "The Cross-Section of Corporate Bond Returns". In: *Working paper*.

Bao, J., M. O'Hara, and X. Zhou (2018). "The Volcker Rule and corporate bond market making in times of stress". In: *Journal of Financial Economics* 130.1, pp. 95–113.

Bartik, T. J. (1991). "Who benefits from state and local economic development policies?" In: *W.E. Upjohn Institute*.

Bavelas, A. (1950). "Communication patterns in task-oriented groups". In: *Journal of the Acoustical Society of America* 22.6, pp. 725–730.

Bessembinder, H., S. Jacobsen, W. Maxwell, and K. Venkataraman (2018). "Capital commitment and illiquidity in corporate bonds". In: *Journal of Finance* 73.4, pp. 1615–1661.

Bessembinder, H., W. Maxwell, and K. Venkataraman (2006). "Market transparency, liquidity externalities, and institutional trading costs in corporate bonds". In: *Journal of Financial Economics* 82.2, pp. 251–288.

Bonacich, P. (1972). "Factoring and weighting approaches to status scores and clique identification". In: *Journal of Mathematical Sociology* 2.1, pp. 113–120.

Bongaerts, Dion, Frank de Jong, and Joost Driessen (2017). "An Asset Pricing Approach to Liquidity Effects in Corporate Bond Markets". In: *Review of Financial Studies* 30.4, pp. 1229–1269.

Brinch, C. N., M. Mogstad, and M. Wiswall (2017). "Beyond LATE with a discrete instrument". In: *Journal of Political Economy* 125.4, pp. 985–1039.

Bruche, M. and C. Gonzalez-Aguado (2010). "Recovery rates, default probabilities, and the credit cycle". In: *Journal of Banking & Finance* 34.4, pp. 754–764.

Chaderina, M. and V. Glode (2023). "Trading with expert dealers". In: *Working paper*.

Chen, Long, David A. Lesmond, and Jason Wei (2007). "Corporate Yield Spreads and Bond Liquidity". In: *Journal of Finance* 62.1, pp. 119–149.

Choi, J., S. Hoseinzade, S. S. Shin, and H. Tehranian (2020). "Corporate bond mutual funds and asset fire sales". In: *Journal of Financial Economics* 138.2, pp. 432–457.

Colliard, J., T. Foucault, and P. Hoffmann (2021). "Inventory management, dealers' connections, and prices in over-the-counter markets". In: *Journal of Finance* 76.5, pp. 2199–2247.

Demiroglu, C., J. R. Franks, and R. Lewis (2022). "Do market prices improve the accuracy of court valuations in Chapter 11?" In: *Journal of Finance* 77.2, pp. 1179–1218.

Di Maggio, M., A. Kermani, and Z. Song (2017). "The value of trading relations in turbulent times". In: *Journal of Financial Economics* 124.2, pp. 266–284.

Dick-Nielsen, J., P. Feldhütter, and D. Lando (2012). "Corporate bond liquidity before and after the onset of the subprime crisis". In: *Journal of Financial Economics* 103.3, pp. 471–492.

Dick-Nielsen, J. and T. K. Poulsen (2019). "How to clean Academic TRACE data". In: *SSRN Electronic Journal*.

Dick-Nielsen, J., T. K. Poulsen, and O. Rehman (2023). "Dealer networks and the cost of immediacy". In: *SSRN Electronic Journal*.

Dick-Nielsen, J. and M. Rossi (2019). "The cost of immediacy for corporate bonds". In: *Review of Financial Studies* 32.1, pp. 1–41.

Dick-Nielsen, Jens, Peter Feldhütter, Lasse Heje Pedersen, and Christian Stolborg (2024). "Corporate Bond Factors: Replication Failures and a New Framework". In: *Working paper*.

Dickerson, Alexander, Philippe Mueller, and Cesare Robotti (2023). "Priced risk in corporate bonds". In: *Journal of Financial Economics* 150.2, p. 103707.

Dickerson, Alexander and Yoshio Nozawa (2024). "Pricing Corporate Bonds with Credit Risk Primitives". In: *Working paper*. UNSW Business School and University of Toronto.

Duffie, D., N. Garleanu, and L. H. Pedersen (2005). "Over-the-counter markets". In: *Econometrica* 73.6, pp. 1815–1847.

Edwards, A. K., L. E. Harris, and M. S. Piwowar (2007). "Bond market transaction costs and transparency". In: *Journal of Finance* 62.3, pp. 1421–1451.

Ellul, A., C. Jotikasthira, and C. T. Lundblad (2011). "Regulatory pressure and fire sales in the corporate bond market". In: *Journal of Financial Economics* 101.3, pp. 596–620.

Feldhütter, P. (2012). "The same bond at different prices: Identifying search frictions and selling pressures". In: *Review of Financial Studies* 25.4, pp. 1155–1206.

Feldhütter, P., E. Hotchkiss, and O. Karakaş (2016). "The value of creditor control in corporate bonds". In: *Journal of Financial Economics* 121.1, pp. 1–27.

Franks, J. R. and W. N. Torous (1994). "A comparison of financial recontracting in distressed exchanges and chapter 11 reorganizations". In: *Journal of Financial Economics* 35.3, pp. 349–370.

Freeman, L. C. (1977). "A set of measures of centrality based on betweenness". In: *Sociometry* 40.1, pp. 35–41.

Friewald, N. and F. Nagler (2019). "Over-the-counter market frictions and yield spread changes". In: *Journal of Finance* 74.6, pp. 3217–3257.

Gertner, R. and D. Scharfstein (1991). "A Theory of Workouts and the Effects of Reorganization Law". In: *Journal of Finance* 46.4, pp. 1189–1222.

Glode, V. and C. Opp (2016). "Asymmetric information and intermediation chains". In: *American Economic Review* 106.9, pp. 2699–2721.

— (2019). "Over-the-counter versus limit-order markets: The role of traders' expertise". In: *Review of Financial Studies* 33.2, pp. 866–915.

Goldberg, J. and Y. Nozawa (2021). "Liquidity supply in the corporate bond market". In: *Journal of Finance* 76.2, pp. 755–796.

Goldstein, I., H. Jiang, and D. T. Ng (2017). "Investor flows and fragility in corporate bond funds". In: *Journal of Financial Economics* 126.3, pp. 592–613.

Goldstein, M. A. and E. S. Hotchkiss (2020). "Providing liquidity in an illiquid market: Dealer behavior in US corporate bonds". In: *Journal of Financial Economics* 135.1, pp. 16–40.

Goldstein, M. A., E. S. Hotchkiss, and E. R. Sirri (2007). "Transparency and liquidity: A controlled experiment on corporate bonds". In: *Review of Financial Studies* 20.2, pp. 235–273.

Heckman, J. J. (1979). "Sample selection bias as a specification error". In: *Econometrica* 47.1, pp. 153–161.

Heckman, J. J., J. Smith, and N. Clements (1997). "Making the Most Out of Programme Evaluations and Social Experiments: Accounting for Heterogeneity in Programme Impacts". In: *Review of Economic Studies* 64.4, pp. 487–535.

Heckman, James J. and Edward J. Vytlacil (2007). "Econometric Evaluation of Social Programs, Part II: Using the Marginal Treatment Effect to Organize Alternative Econometric Estimators to Evaluate Social Programs, and to Forecast their Effects in New". In:

Handbook of Econometrics. Ed. by J.J. Heckman and E.E. Leamer. Vol. 6. Handbook of Econometrics. Elsevier. Chap. 71.

Hendershott, T., D. Li, D. Livdan, and N. Schürhoff (2020). "Relationship trading in over-the-counter markets". In: *Journal of Finance* 75.2, pp. 683–734.

Hollifield, B., A. Neklyudov, and C. Spatt (2017). "Bid-ask spreads, trading networks, and the pricing of securitizations". In: *Review of Financial Studies* 30.9, pp. 3048–3085.

Hotchkiss, Edith S. and Robert M. Mooradian (1997). "Vulture investors and the market for control of distressed firms". In: *Journal of Financial Economics* 43.3, pp. 401–432.

Huang, Jing-Zhi Jay, Stefan Lewellen, and Zhe Wang (2024). "Creditor Coalitions in Bankruptcy". In: *Working paper*.

Hugonnier, J., B. Lester, and P.-O. Weill (2019). "Frictional intermediation in over-the-counter markets". In: *Review of Economic Studies* 87.3, pp. 1432–1469.

Ivashina, V., B. Iverson, and D. C. Smith (2016). "The ownership and trading of debt claims in Chapter 11 restructurings". In: *Journal of Financial Economics* 119.2, pp. 316–335.

Jankowitsch, R., F. Nagler, and M. G. Subrahmanyam (2014). "The determinants of recovery rates in the US corporate bond market". In: *Journal of Financial Economics* 114.1, pp. 155–177.

Jiang, Wei, Kai Li, and Wei Wang (2012). "Hedge Funds and Chapter 11". In: *Journal of Finance* 67.2, pp. 513–560.

Kyle, Albert S. (1985). "Continuous auctions and insider trading". In: *Econometrica* 53.6, pp. 1315–1335.

Lewis, R. (2016). "Corporate Debt Markets and Recovery Rates with Vulture Investors". In: *Working paper*.

Li, D. and N. Schürhoff (2019). "Dealer networks". In: *Journal of Finance* 74.1, pp. 91–144.

Lim, Jongha (2015). "The Role of Activist Hedge Funds in Financially Distressed Firms". In: *Journal of Financial and Quantitative Analysis* 50.6, pp. 1321–1351.

Lin, Hai, Junbo Wang, and Chunchi Wu (2011). "Liquidity risk and expected corporate bond returns". In: *Journal of Financial Economics* 99.3, pp. 628–650.

Longstaff, Francis A., Sanjay Mithal, and Eric Neis (2005). "Corporate Yield Spreads: Default Risk or Liquidity? New Evidence from the Credit Default Swap Market". In: *Journal of Finance* 60.5, pp. 2213–2253.

May, A. D. (2010). "The impact of bond rating changes on corporate bond prices: New evidence from the over-the-counter market". In: *Journal of Banking & Finance* 34.11, pp. 2822–2836.

Mora, N. (2015). "Creditor recovery: The macroeconomic dependence of industry equilibrium". In: *Journal of Financial Stability* 18, pp. 172–186.

Nagler, F. and G. Ottonello (2023). "A Corporate Finance View of Debt Market Illiquidity". In: *Working paper*.

Nazemi, A. and F. J. Fabozzi (2018). "Macroeconomic variable selection for creditor recovery rates". In: *Journal of Banking & Finance* 89, pp. 14–25.

Reichenbacher, M. and P. Schuster (2022). "Size-adapted bond liquidity measures and their asset pricing implications". In: *Journal of Financial Economics* 146.2, pp. 425–443.

Sambalaibat, B. (2022). "Endogenous specialization and dealer networks". In: *Working paper*.

Varma, P. and R. Cantor (2005). "Determinants of recovery rates on defaulted bonds and loans for North American corporate issuers: 1983-2003". In: *Journal of Fixed Income* 14.4, pp. 29–44.

Wruck, Karen Hopper (1990). "Financial distress, reorganization, and organizational efficiency". In: *Journal of Financial Economics* 27.2, pp. 419–444.

Appendix A Sample Construction

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 the offering amount, days to maturity at default, coupon rate, covenant information, and bond ratings one year before 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 before default. This includes equity value, the number of employees, and both short and long-term debt 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 executed during the sample period.[2] This 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 to

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

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

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 can 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 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

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

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

to Figure A.1 for an illustration of the non-randomness in dealer connectedness based on in- and out-degree centrality.

For 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 before 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 before default, each of these bonds is bought by an average (median) of 53 (39) unique dealers, and during the 30 days after default by an average (median) of only about 20 (11) dealers, indicating a concentration

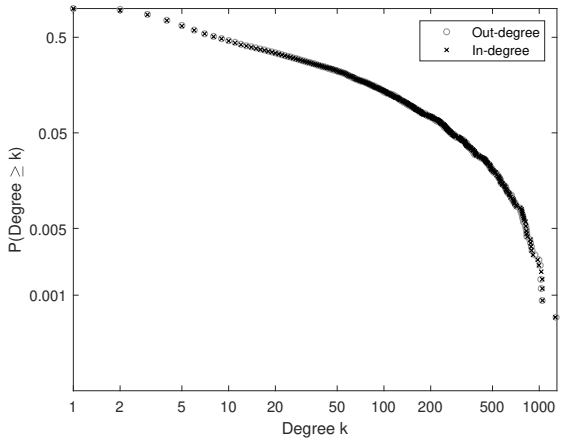


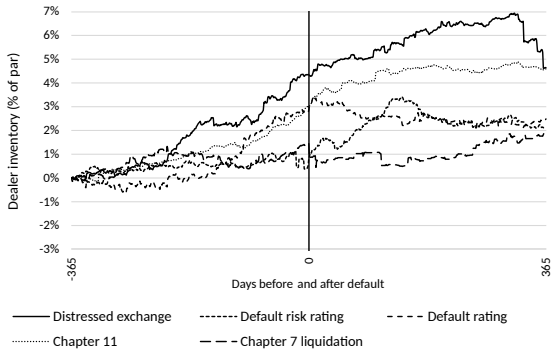
Figure A.1: The figure illustrates the inverse in- and out-degree centrality distribution of the 3,383 bond dealers that form the dealer network. Out-degree centrality is represented by circles and in-degree centrality by cross-marks. The figure is log-scaled and shows that the centrality distribution 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.

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.

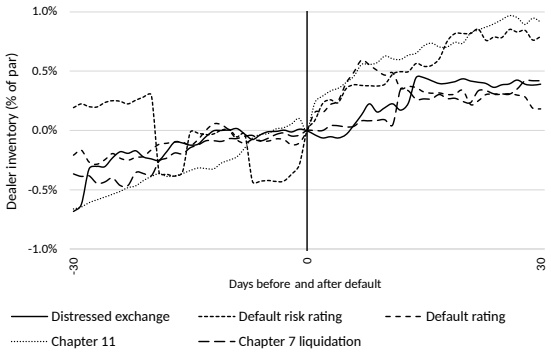
Determining agency trades. For each bond transaction reported in TRACE data, an indicator denotes agency trades in which dealers prearrange the trades in a broker role without taking inventory risk. These agency trades represent about 8% of all transactions reported to TRACE in our data. However, as a standard convention in the literature, 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). A dealer may split 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 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. 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 daily 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 one year before default (Panel A) and on the default day (Panel B), respectively.



(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.

Appendix B Trade-Based Recovery Rates

Table 4 reports regression results for trade-level recovery rates. To control for potential endogeneity and selection bias, we use several IV approaches. Here we discuss these additional specifications.

Alternative ways to measure primary dealers' impact on recovery rates. To account for the fact that the primary dealer status is an endogenous choice and outcome of the investor-dealer matching process we consider the following empirical model. 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-specific impact on intermediating the bond via her skill and expertise

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

An important empirical question is whether the primary dealer's impact on the recovery rate $\beta \equiv RR^1 - RR^0$, 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, $\beta \geq 0$, or value-destroying, $\beta < 0$. 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 β 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^d_{ij}. For clarity, we assume linearity of the expected recovery term $\mu^d(X_{ij})$:

$$RR^d_{ij} = \alpha + \beta\, PrimaryDealer_{ij} + \delta' X_{ij} + \epsilon^d_{ij}, \quad d = 0, 1. \tag{B.2}$$

Observed recoveries in our sample can be decomposed as

$$RR_{ij} = (1 - PrimaryDealer_{ij}) \times RR^0_{ij} + PrimaryDealer_{ij} \times RR^1_{ij}. \tag{B.3}$$

Specifics of estimating β (and the recovery rate determinants δ) depend 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.

A potential concern with explaining trade-level recovery rates (B.3) 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 in our empirical specification, 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 before default, similar to equation (1) in Section (1.2). It captures the ownership concentration before default, and thus proxies supply-induced selling pressure in a given bond which amplifies investors' needs to find specialized dealers that still provide liquidity.[1] 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, hence satisfying the exclusion restriction.[2]. 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,

[1] While ownership concentration during the distressed debt resolution process has a positive effect on the distress resolution outcomes (see, for example, Gertner and Scharfstein (1991), Ivashina, Iverson, and Smith (2016) or Feldhütter, Hotchkiss, and Karakaş (2016)), our approach is to identify the recovery rates obtained by investors who well immediately following default, and thus do not take part in the distress resolution process.

[2] The exclusion restriction could be violated if OTC prices obtained from primary dealers were not market prices that are the result of investors' and dealers' choice of trading with each other, which contradicts prior research (see, for example, Acharya, Bharath, and Srinivasan (2007))

the propensity to trade with a primary dealer equals: $\Pr(PrimaryDealer_{ij}|\text{HHI}_j, X_{ij}) = P(\alpha + \theta\,\text{HHI}_j + \gamma' X_{ij})$, 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 (3). To implement the primary dealer choice in our data, we estimate in the first stage the following Probit model: $\Pr(PrimaryDealer_{ij}|\text{HHI}_j, X_{ij}) = \Phi(\alpha + \theta\,\text{HHI}_j + \gamma'\,X_{ij})$. In the second stage, we use in specification (3) the predicted value $\widehat{PrimaryDealer}_{ij} = \widehat{\Pr}(PrimaryDealer_{ij})$ from the first stage specification instead of indicator $PrimaryDealer_{ij}$. In the first stage, the instrument is highly 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, 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. Thus, ownership concentration is a strong instrument to augment the propensity of trading with primary dealers after default.

Alternative instruments. 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 3 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.

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 who 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

$$K(p) = pK^1(p) + (1-p)K^0(p). \tag{B.4}$$

$K^d(p)$ are unspecified functions of the propensity score p with two regularity conditions: $\lim_{p\to 0} K^1(p) = 0$, $\lim_{p\to 1} K^0(p) = 0$.[3]

We can estimate the primary dealer's premium/discount β and determinants β of recovery rates in the sample of trades with primary and non-primary dealers by recognizing that

$$RR^d_{ij} = \alpha + \beta\, PrimaryDealer_{ij} + K^d(p_{ij}) + \beta' X_{ij} + \varepsilon^d_{ij}, d = 0, 1, \tag{B.5}$$

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):[4]

$$RR_{ij} = \alpha + \beta\, PrimaryDealer_{ij} \times p_{ij} + \lambda\, K(p_{ij}) + \beta' X_{ij} + \varepsilon_{ij}, \tag{B.6}$$

with mean-zero error ε_{ij} and $K(p_{ij})$ is the Mills term defined in (B.4) and treated as an unspecified function of the propensity of trading with a primary dealer during a bond default. $K(p) \leq 0$ 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 in Tables B.1 and B.2 reports results from specification (B.6). The propensity to trade with a primary dealer, p_{ij}, is estimated from the Probit model in Section 2.1. The negative and statistically significant coefficient on p_{ij} and positive and statistically significant coefficient on p^2_{ij} indicate essential heterogeneity in the propensity to transact with primary dealers.

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

[4] 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.

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 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)
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
Specification	1st stage	OLS	Saturated	IV	Heckman	MEH
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 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)
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
Specification	1st stage	OLS	Saturated	IV	Heckman	MEH
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

Primary dealer definition. So far we have considered the dealer that intermediates the largest number of trades in a defaulted bond during the year before default as the primary dealer. To check the robustness of this primary dealer measure, we consider alternative definitions. One possible caveat of the primary dealer as defined in the paper is that the primary dealer's expertise is not bond-related, but related to the firm. Thus, instead of defining the primary dealer based on the number of trades in a given bond, we alternatively define the primary dealer as the dealer that intermediates the largest number of trades in any bond of the firm that issued the defaulted bond.

Table B.3 presents the regression results. The left column of Table B.3 shows that the instrument is not significant with this alternative definition of primary dealer. Neither when we consider other instruments, as in Tables B.1 and B.2, will we yield a significant instrument. Thus, while the OLS estimates yield consistent results as our main analysis, we do not find that there is a shift towards trading with dealers that have expertise related to the firm, as opposed to the defaulted bond, because the instrument is not valid in this case.

Because the primary dealer is sometimes the bond's underwriter, we check whether defining the underwriter as the primary dealer will yield consistent results. As dealer identities are masked in our TRACE data, and thus the underwriter characteristic cannot be directly observed, we proxy for the underwriter characteristic such that we define the dealer as an underwriter who intermediates the largest number of trades of a defaulted bond during the year after the bond's issuance, and which is not at the same time a primary dealer as defined in our main analysis. The results in Table B.4 show that the underwriter characteristics do not explain the primary dealers' effects on the pricing of defaulted corporate bonds, nor do we find that trading shifts towards underwriters after default.

Volcker Rule. As an additional robustness check, we investigate whether the introduction of the Volcker Rule impacts primary dealers' defaulted bond pricing implications. Therefore, we add a dummy variable to the regressions in Table 4, indicating whether a trade happens after the implementation of the Volcker Rule on April 1, 2014. As the results indicate, recovery rates are about 11 to 13 cents lower per dollar invested after implementation of the Volcker Rule, potentially given that dealers are less likely to absorb excess supply due to stricter regulations prohibiting excess risk-taking on dealers' own balance sheets.

Table B.3: **Trade-based recovery rates—alternate primary dealer 1.** The left column is the Probit specification that estimates the probability of clients trading with primary dealers when selling recently defaulted bonds to create the instrumental *PrimaryDealer* variable. The binary *PrimaryDealer* variable indicates whether the bond is sold to a primary dealer. The primary dealer is here defined as the dealer that intermediates the largest number of trades of a given firm. 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)
PrimaryDealer ($\times p$ in (5))		2.98**	2.91**	6.01	2.39**	16.59**
Lambda					−81.88***	
p						86.21**
p^2						−94.02
Pre-default HHI	0.02					
LargeInstitutional	−0.06	−0.02	−1.17*	−0.04	0.23	0.29
Retail	0.01	0.20	0.23	0.23	0.23	0.17
Distressed exchange	0.13	13.13***	11.61**	13.32***	9.76**	9.28*
Risk rating	0.02	15.12***	14.56***	15.27***	13.08***	12.62**
Chapter 11	−0.22	−1.31	−2.27	−1.29	−1.24	−1.06
Chapter 7 liquidation	0.15	1.78	0.01	1.81	0.85	0.32
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
Specification	1st stage	OLS	Saturated	IV	Heckman	MEH
R^2		0.5906	0.6184	0.5899	0.5931	0.5935
# observations	108.536	108.536	108.536	108.536	108.536	108.536

Table B.4: **Trade-based recovery rates—underwriter.** The left column is the Probit specification that estimates the probability of clients trading with the bond's underwriter when selling recently defaulted bonds to create the instrumental *Underwriter* variable. The binary *Underwriter* variable indicates whether the bond is sold to the bond's underwriter. 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%).

	$Underwriter_{ij}$	Trade-level recovery rate RR_{ij}				
		(1)	(2)	(3)	(4)	(5)
Underwriter ($\times p$ in (5))		−1.03	1.19*	−2.03	−0.83	−7.43
Lambda					87.71***	
p						−69.09
p^2						53.10
Pre-default HHI	0.22					
LargeInstitutional	−0.06	−0.13	−1.40**	−0.12	−0.66	−0.70
Retail	−0.29***	0.62	0.57	0.66	−1.16	−1.36
Distressed exchange	0.01	17.56***	16.19***	17.57***	17.39***	17.34***
Risk rating	−0.11	21.33***	20.95***	21.35***	20.57***	20.44***
Chapter 11	0.04	2.73	1.98	2.74	2.36	2.34
Chapter 7 liquidation	0.88**	8.66	6.27	8.54	15.22	15.47
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
Specification	1st stage	OLS	Saturated	IV	Heckman	MEH
R^2		0.5683	0.6002	0.5681	0.5697	0.5697
# observations	87.196	87.196	87.196	87.196	87.196	87.196

Table B.5: **Trade-based recovery rates—Volcker Rule.** The left column is the Probit specification that estimates the probability of clients trading with primary dealers when selling recently defaulted bonds to create the instrumental *PrimaryDealer* variable. The binary *PrimaryDealer* variable indicates whether the bond is sold to a primary dealer. The *VolckerRule* indicator captures whether a trade happens after the implementation of the Volcker Rule on April 1, 2014. 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)
PrimaryDealer ($\times p$ in (5))		4.49***	2.03***	6.68***	4.25***	7.68***
Lambda					−6.51	
p						−22.06*
p^2						22.41***
Pre-default institutional HHI	0.78***					
Volcker Rule	0.00	−12.85**	−12.24**	−12.68**	−12.71**	−12.71**
LargeInstitutional	0.16	−0.19	−1.22**	−0.38	−0.31	−0.15
Retail	0.51***	−0.26	0.24	−0.31	−0.59	0.60
Distressed exchange	1.02***	12.65***	11.91**	11.92**	11.92**	14.78***
Risk rating	0.96***	13.95***	14.19***	13.25***	13.32**	15.35***
Chapter 11	0.71***	−2.29	−2.52	−3.21	−2.80	−1.17
Chapter 7 liquidation	1.29	0.89	0.02	−0.09	0.01	2.72
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
Specification	1st stage	OLS	Saturated	IV	Heckman	MEH
R^2		0.5979	0.6201	0.5962	0.5981	0.6028
# observations	108.536	108.536	108.536	108.536	108.536	108.536

Appendix C Derivation of Results 1 and 2

In deriving the recursion for A_I, we have used that $\mathbb{E}[D_i] = \mathbb{E}[D_i^2] = p$ and that $\mathrm{Cov}(D_i, \pi_{i\pm1}) = 0$. To prove Result 1 we rewrite the expression (13) as

$$\beta^{\mathrm{TL}} = b + c\frac{B_{I,I}}{p(1-p)}, \tag{C.1}$$

where

$$\begin{aligned} B_{I,I} &\equiv \mathrm{Cov}(D_i, \pi_i) = \mathbb{E}[D_i\pi_i] - p\mathbb{E}[\pi_i] = \\ &= pA_{I-1} + \alpha\mathbb{E}[D_i^2] - \delta A_{I-1}\mathbb{E}[D_i - D_i^2] + \rho A_{I-1}\mathbb{E}[D_i^2] - \\ &\quad - pA_{I-1} - \alpha p^2 - \delta A_{I-1}p(1-p) - \rho p A_{I-1} = \\ &= p(1-p)\left[\alpha + (\rho - \delta)A_{I-1}\right], \end{aligned}$$

thus resulting in the expression (14).

For the bond-level regression coefficient, we need to calculate the covariances in (17). We start by noting that $\mathrm{Cov}(D_{i+1}, \pi_i) = 0$. Then we have using (9) that

$$\mathrm{Cov}(D_{i-1}, \pi_i) = \kappa B_{i-1,i-1}, \tag{C.2}$$

and

$$\mathrm{Cov}(D_{i-2}, \pi_i) = \kappa\mathrm{Cov}(D_{i-2}, \pi_{i-1}) = \kappa^2 B_{i-2,i-2}, \tag{C.3}$$

and, finally, using the induction

$$\mathrm{Cov}(D_1, \pi_i) = \kappa^{i-1} B_{1,1}. \tag{C.4}$$

Therefore, the numerator in the second ratio in (17) can be written as

$$\begin{aligned}\frac{\mathrm{Cov}(\sum_{i=1}^{I+1} RR_i, \sum_{i=1}^{I+1} D_i)}{p(1-p)} &= (1+...+\kappa^I)B_{1,1} + (1+...+\kappa^{I-1})B_{2,2} + ... + (1+\kappa)B_{I,I} + \\ &+ B_{I+1,I+1} = \alpha\left[1 + \frac{1-\kappa^2}{1-\kappa} + ... + \frac{1-\kappa^{I+1}}{1-\kappa}\right] + \\ &- (\delta-\rho)\left[A_I + \frac{1-\kappa^2}{1-\kappa}A_{I-1} + ... + \frac{1-\kappa^{I+1}}{1-\kappa}A_0\right] = \\ &= \frac{\alpha}{1-\kappa}\left[1-\kappa+1-\kappa^2+...+1-\kappa^{I+1}\right] + \\ &- \frac{(\delta-\rho)A_I}{1-\kappa}\left[1-\kappa+(1-\kappa^2)\frac{A_{I-1}}{A_I} + ... + (1-\kappa^{I+1})\frac{A_0}{A_I}\right] = \\ &= \frac{\alpha}{1-\kappa}\left[I+1-\frac{\kappa(1-\kappa^{I+1})}{1-\kappa}\right] + \\ &- \frac{(\delta-\rho)A_I}{1-\kappa}\left[1-\kappa+(1-\kappa^2)\frac{A_{I-1}}{A_I} + ... + (1-\kappa^{I+1})\frac{A_0}{A_I}\right].\end{aligned}$$

Consider now the large-sample limit $I \to \infty$. We immediately have that $A_\infty = \alpha p/(1-\kappa)$ as well as

$$A_I = A_\infty - \kappa^I(A_\infty - A_0) \Rightarrow \frac{A_I}{A_\infty} = 1 - \kappa^I(1 - \frac{A_0}{A_\infty}). \tag{C.5}$$

Then we have

$$\begin{aligned}&1-\kappa+(1-\kappa^2)\frac{A_{I-1}}{A_I} + ... + (1-\kappa^{I+1})\frac{A_0}{A_I} \\ &\qquad\approx 1-\kappa+(1-\kappa^2)\frac{A_{I-1}}{A_\infty} + ... + (1-\kappa^{I+1})\frac{A_0}{A_\infty} \\ &= 1-\kappa+(1-\kappa^2)(1-\kappa^{I-1}(1-\frac{A_0}{A_\infty})) + ... + (1-\kappa^{I+1})(1-\kappa^0(1-\frac{A_0}{A_\infty})) \\ &\qquad = I+1+\left(\kappa^{I+1} - \frac{1-\kappa^I}{1-\kappa}\right)(1-\frac{A_0}{A_\infty}) - \frac{\kappa(1-\kappa^{I+1})}{1-\kappa},\end{aligned}$$

which is of the order of $I+1$ when I is large. We, therefore, have in the large I limit

$$\frac{\mathrm{Cov}(\sum_{i=1}^{I+1} RR_i, \sum_{i=1}^{I+1} D_i)}{p(1-p)} \approx \frac{I+1}{1-\kappa}(\alpha + (\rho-\delta)A_I), \tag{C.6}$$

leading to the regression coefficient

$$\beta^{\mathrm{BL}}_{I\to\infty} = b + \frac{c}{1-\kappa}(\alpha + (\rho - \delta)A_\infty). \tag{C.7}$$