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Are CDS Auctions the Tail Wagging the Dog? An Empirical Study of Corporate Bond Return Volatility at the Time of Default

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Abstract

Over the past decade, numerous engineered credit events and cases of market participants manipulating bond prices to influence CDS auction payouts have occurred. These cases have become increasingly common, and the CFTC has stated they may constitute market manipulation and undermine not only the CDS market but also the credit derivative and default markets. Although there is a plethora of news and media coverage on publicized cases, there is no previous empirical research on evidence of these practices. This paper is motivated by the desire to determine if there is indirect evidence of bond price manipulation around default and of market participants' attempts to favorably move CDS's underlying bond prices to achieve more profitable positions around default and emerging from CDS auctions. The analysis is performed by analyzing the effect of a bonds' inclusion in CDS auctions on bond return volatility around the time of default while controlling for credit risk, illiquidity, firm fundamentals, and other bond-level controls. I find that bond return volatility around default is much higher as a result of a bond's inclusion in a CDS auction, which serves as indirect evidence of bond price manipulation around default as market participants strive for more profitable CDS auction outcomes and possibly of manufactured credit events. Consistent with previous literature, I also find that bond illiquidity significantly impacts bond return volatility. My results are robust to propensity score matching, implementing double-robust estimators, and controlling for any time-varying cross-sectionally-invariant fluctuations in bond return volatility.

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1. Introduction

"The gambit is fiendlishly clever. It is the debt equivalent of a controlled explosion: offering a struggling company favourable financing … to convince it to intentionally default in a way that will trigger payouts on CDS contracts, but without bringing down the whole company."

- Financial Times (June 2018)[1]

Credit default swaps (CDS) are default insurance contracts that aim to transfer the credit exposure of bonds and other fixed income products between buyers of protection (CDS buyers) and sellers of protection (CDS sellers). CDS are one of the most significant financial product developments in the past 25 years, gaining not only pervasiveness but also regulation and policy scrutiny since creation. Since their creation in 1994 by JPM, CDS have been used by investors for a variety of purposes, ranging from insurance and hedging to speculation and arbitrage. Although originally intended as a method of insurance and default risk mitigation for banks, CDS have increasingly become used in speculation and arbitrage by banks, hedge funds, and other financial institutions. According to the Bank of International Settlements (BIS), as of December 2017, global CDS markets have a notional amount outstanding of $9.354 trillion and a gross market value of $304 billion. This is down from $61.2 trillion notional outstanding at the end of 2007 before the Great Financial Crisis.[2]

The Great Financial Crisis drew significant attention to CDS and other credit derivatives after the high number of large-scale incidents in 2008, beginning with the collapse of Bear Stearns. In 2008, CDS trades were executed over the counter (OTC),

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[1] *The Financial Times*, 2018, "Debt equivalent of a controlled explosion helped Blackstone edge out rivals," Jun 5.

[2] See the semiannual OTC derivatives statistics, Bank for International Settlements, December 2017.

because a central exchange or clearing house did not exist. This prompted the Depository Trust & Clearing Corporation (DTCC) to publish information on CDS trades on a weekly basis (DTCC (2008)).[3] Previously, in 2001, data provider Markit had also made pricing and other information available on CDS contracts. In addition to increased transparency, the CDS market experienced several other fundamental changes to address concerns about the product's risk after 2008, accommodate market growth, and improve efficiency. More specifically, the International Swaps and Derivatives Association (ISDA) introduced (1) central clearing houses (the counterparty to both sides of a CDS transaction) operated by the InterContinental Exchange (ICE) to reduce the counterparty risk faced by both buyers and sellers, and (2) the international standardization of CDS contracts (known as the "CDS Big Bang") to improve the infrastructure of the CDS market and improve efficiency (Markit (2009)). Ultimately, the industry experienced consequential change in market size and structure over the course of several months, and even greater change over the last decade (Aldasoro and Ehlers (2018)).

The success of these reforms to decrease risk and increase transparency and regulation relies on understanding how the CDS market operates and the efficiency of the market (Chernov, Gorbenko, Makarov (2013)). As a result, there has been significant research on CDS premia and spreads (Longstaff, Mithal, and Neis (2005)), default and recovery from the term structure of CDS spreads (Jaskowski and McAleer (2012), Pan and Singleton (2008)), CDS valuation (Duffie (1999)), insider trading (Acharya and Johnson (2007)), counterparty risk (Arora, Gandhi, and Longstaff (2009); Duffie and Zhu (2011)), and other topics on the CDS market. More recently, some research has been devoted to

[3] See DTCC, 2008, Global Trade Repository, *OTC Derivative Reporting*.

understanding CDS auctions and settlements and their possible biases and inefficiencies. Specifically, Chernov, Gorbenko, and Makarov (2013) and Du and Zhu (2016) analyze the two-stage CDS auction design theoretically and empirically and determine that the current auction design results in biased bond prices and inefficient allocations.

Despite the targeted CDS market reforms and research on CDS auctions and settlement procedures, there remains inefficiencies, biases, and manipulations. Since 2009, there have been several cases of bond price manipulation influencing CDS payouts and "engineered credit events." In an engineered credit event, a market participant synthetically triggers (manufactured credit event) or prevents (debt orphaning or other CDS manipulation) the payout of a company's CDS to benefit one or more financial institutions and/or the company. There are also cases where market participants, usually CDS buyers or sellers, push for better positions emerging from CDS auctions, namely by moving bond prices favorably before the auction. For example, in Goldman's duel with GSO (Blackstone Group's credit hedge fund unit), it tried to push up the bond price to reduce its payout on Hovnanian CDS after GSO helped manufacture Hovnanian's credit event.

Although these manipulation cases have become more common, with three public cases in the past twelve months (Hovnanian, Sears, and McClatchy), they are neither explicitly fair market activity nor using CDS for the way in which it was designed. According to the Commodity Futures Trading Commission (CFTC), they may constitute market manipulation and undermine not only the CDS market but also the credit derivative and default markets.[4] Following the Hovnanian credit event, Simon Firth, a partner at

[4] Doran, Josh, 2018, "Manufactured Credit Events May 'Damage' CDS Market: CFTC," *IFRe*, Apr 25.

Linklaters, said to IFR (International Financing Review), "it is significant because if manufactured defaults were to happen left, right and center, that could cause a collapse of confidence in the credit derivative market."[5] Further conversation and casual empiricism suggest that the ramifications of engineered credit events and bond price manipulation could lead to decreased confidence in the CDS market, lower levels of trading activity, increased hedging risk, greater marketplace inefficiencies, and reduced market transparency.

This paper is motivated by the desire to determine if there is indirect evidence of bond price manipulation around default and of market participants' attempts to favorably move CDS's underlying bond prices to achieve more profitable positions around default and emerging from CDS auctions. This paper fills the gap in existing literature on the study of empirical evidence of such manipulation and will be the first to examine bond return volatility around the time of default. Previous research into direct evidence of these practices is sparse because of the limited data and small number of revealed cases (Hovnanian, Sears, McClatchy, etc.), but CDS's reference securities provide more data that can be used to investigate possible evidence of market participants manipulating the market.

This paper aims to determine if there is indirect evidence of the manipulation of CDS's underlying bond prices by comparing the volatility of bond returns around the time of default for bonds that are included in CDS auctions (either because they have CDS written on them or their reference entity does). This analysis is performed by computing

[5] Scigliuzzo, Davide, 2018, "CFTC Steps into Debate on Voluntary Defaults," *Thomson Reuters*, Apr 27.

bond return volatility from before default to when a CDS auction would typically occur and running regressions motivated by Bao and Pan (2013), with controls for credit risk, illiquidity, firm fundamentals, and other bond-level controls. Propensity score matching, double robust estimators, and regressions with time fixed-effects are then used to further determine the effect of CDS auction on bond return volatility and as robustness tests.

Looking at bond return volatility rather than just abnormal bond returns is motivated by Goldman and GSO's duel in which both firms tried to manipulate bond prices before the CDS auction but in opposite directions. Thus, for each reference security, it is unknown what hedge funds' net CDS or bond positions are at the time of default, and therefore which direction they are attempting to move prices. Further, because there are participants on both sides of the trade, there are likely efforts to move prices in both directions, thus creating abnormal return volatility but not necessarily net abnormal returns.

I hypothesize that if bond price manipulation and/or manufactured credit events are present, the bond return volatility will be higher for bonds that are included in CDS auctions than their counterparts that are not because of market participants' attempts to move prices favorably both prior to auction and prior to default. The bond default data and bond pricing data for this paper are collected from Moody's Default and Recovery Database (DRD) and FINRA's TRACE (Transaction Reporting and Compliance Engine), respectively. The bond data is matched to Compustat to obtain firm fundamental data. The CDS data is obtained from Markit and the other data is collected from regular data sources, such as CRSP, U.S. Treasury's Constant Maturity Treasury (CMT) series, and Bloomberg.

First, this paper contributes to the increasing evidence of and debate over manufactured credit events. To my knowledge, this paper is the first to make a rigorous attempt to uncover evidence of market participants manipulating bond prices around default and in CDS auctions. Notably, this paper finds indirect empirical evidence of the manipulation of bond returns for bonds in CDS auctions and therefore possibly manufactured credit events. I use bond return volatility as a measure of indirect evidence of market participants manipulating bond returns before default and from default to auction to achieve more profitable positions emerging from CDS auctions. The average annual bond return volatility across all bonds around the time of default is 99.6% to 139.8%. After controlling for bond illiquidity, credit risk, firm fundamentals, and other bond-level controls using baseline regressions, I find that a bond included in a CDS auction is associated with a higher bond return volatility of 31.2 to 63.8 percentage points around the time of default, with the highest CDS auction bond volatility in the six months prior to default.

These results are robust to propensity score matching (PSM), in which a CDS auction is associated with a greater annual volatility of 26.2 to 114.0 percentage points.[6] Using PSM, I measure the average treatment effect on the treated (ATET or ATT) and average treatment effect (ATE). I estimate that the average bond return volatility for a CDS auction bond is 75.4 to 157.5 percentage points higher than if it is not in a CDS auction (ATET) and that the bond return volatility around the time of default is 63.7 to 191.1 percentage points higher when a bond is included in a CDS auction (ATE), depending on the time period around default. Furthermore, these results persist when using double-robust estimators. The ATE calculated using double-robust estimators of CDS auction on bond

[6] Measured using the PSM matched sample based on bonds' propensity to be included in CDS auction and running the same baseline regressions as done with the unmatched sample.

return volatility estimates that bond return volatility around the time of default is 14.6 to 75.7 percentage points higher when a bond is in a CDS auction. Lastly, to control for any time-varying cross-sectionally-invariant variations in bond return volatility that are potentially unexplained by my controls, such as market-wide fluctuations, I run my baseline regressions with time fixed-effects. I find that CDS auction is significantly positively related to bond return volatility with time fixed-effects and positively related to bond return volatility with time fixed effects and standard errors clustered by distinct default event. This paper therefore finds that bond return volatility around default is higher as a result of a bond's inclusion in a CDS auction, serving as indirect evidence of bond price manipulation around default as market participants strive for more profitable CDS auction outcomes and possibly manufactured credit events.

Second, this paper contributes to the growing literature on CDS pricing and trading, ties between CDS auctions and bond pricing at default, and corporate bond return volatility. Although there has been a large amount of studies on the CDS auction settlement procedure (Chernov, Gorbenko, and Makarov (2013); Du and Zhu (2016); Gupta and Sundaram (2011); and Peivandi (2015)) and structural models of default (Jones, Mason, and Rosenfeld (1984); Eom, Helwege, and Huang (2004)), and the credit spread puzzle (Huang and Huang (2003); Elias, Hellwig, and Tsyvinski (2014), Bhar and Handzic (2008); and Feldhutter and Schaefer (2018); Bao and Pan (2013); and Chen, Lesmond, and Wei (2007)), there is only one paper to my knowledge connecting CDS auctions and bond pricing at default (Helwege et al. (2009)). Thus, this paper is the first to model factors influencing bond return volatility around the time of default and investigate the effect of a bond's inclusion in a CDS auction on bond return volatility before and after default. The results of this paper suggest bond illiquidity and a bond's inclusion in a CDS auction have the greatest significant impact on bond return volatility around the time of default. Only some firm fundamentals are significantly related to bond return volatility for the two of the time periods around default. However, the firms I am analyzing are all near default, and so there is not a wide range of firm attributes as there is in Bao and Pan (2013).

Although there is little research examining bond returns and volatility around the time of default, there is extensive research on corporate bond returns and volatility, return and volatility factors, and credit spreads. Significant research focuses on structural models of default; Jones, Mason, and Rosenfeld (1984) and Eom, Helwege, and Huang (2004) find that these structural models do not match the magnitudes of credit spreads. Specifically, Huang and Huang (2003) determine that numerous structural models underestimate corporate bond yield spreads when matched to historical default probabilities. This dislocation, named "the credit spread puzzle," has attracted significant research since Huang and Huang (2003). This research endeavors to explain the credit spread puzzle, particularly through model dynamics, see for example Elias, Hellwig, and Tsyvinski (2014), Bhar and Handzic (2008), and Feldhutter and Schaefer (2018). Alternative literature suggests an illiquidity component, such as in Bao and Pan (2013) and Chen, Lesmond, and Wei (2007).

The remainder of the paper is organized as follows. Section 2 offers a review of the literature on CDS auction settlement structure, inefficiencies, and biases; structural models of default; and measuring excess price volatility and its determinants. Section 3 presents a review of the news stories on publicized manufactured and engineered credit events while Section 4 provides a detailed description of the current CDS auction structure. Section 5 describes the databases used, the creation of the dataset, variable construction, and the dataset, and Section 6 provides the empirical strategy used in this paper. Section 7 presents and explains the empirical results using baseline regressions, propensity score matching, and double-robust estimators, and Section 8 concludes and offers future research opportunities.

2. Literature Review

While empirical and quantitative research on engineered credit events and bond return volatility is limited, CDS market structure, trading, valuation, and settlement have been studied extensively, see, for example, Longstaff, Mithal, and Neis (2005), Jaskowski and McAleer (2012), Pan and Singleton (2008), Duffie (1999), Acharya and Johnson (2007), Arora, Gandhi, and Longstaff (2009), and Duffie and Zhu (2011). More specifically**,** Chernov, Gorbenko, and Makarov (2013), Du and Zhu (2016), Gupta and Sundaram (2011), and Peivandi (2015) examine CDS auctions and determine biases and inefficiencies resulting from the auction structure. In their seminal paper, Chernov, Gorbenko, and Makarov (2013) (CGM), analyze CDS settlement auctions theoretically and evaluate them empirically. To conduct their analysis, they extend the strategic bidding models of Wilson (1979) and Back and Zender (1993). CGM (2013) determine that, because of strategic bidding from participants holding CDS, the final auction price may be above or below the fair bond price. They calculate undervaluation to occur most commonly, with auctions undervaluing bonds by an average of 6% on the auction day.

Similar to CGM (2013), Gupta and Sundaram (2011) (GS) also find a V-shaped price pattern, where final prices from CDS auctions are lower than bond prices before and after auction dates. GS (2011) also determine that information from the auction, particularly the auction's final price, is integral to price formation after the auction and that bond return volatility typically increases after the auction (compared to pre-auction). They hypothesize that this is due to the entrance of new, informed investors post-auction.

CGM (2013) also shares several common features with Peivandi (2015), but Peivandi (2015) uses a different theoretical model of a mechanism-design approach with emphasis on auction participation. Both CGM (2013) and Peivandi (2015) find price impact in the second stage of the CDS auction, but, Peivandi (2015) also shows the only way to guarantee full participation in CDS auctions is through a fixed price. Thus, full participation and price discovery cannot both be accomplished. Du and Zhu (2016) (DZ) offer complementary results to CGM (2013) and Peivandi (2015), evaluating CDS auctions with both a theoretical and market design perspective. DZ (2016) determine an additional cause of biased prices and inefficient allocations in CDS auctions: specific types of traders are unable to participate due to certain restrictions. DZ (2016) also find that, because a greater CDS position (in absolute value) relieves CDS auction's first stage participation constraints, traders have excessive CDS positions before defaults. Ultimately, CGM, (2013), GS (2011), Peivandi (2015), and DZ (2016) all agree the current design of CDS auctions can lead to biased prices and inefficient allocations.

While the aforementioned papers evaluate the design of CDS auctions, Helwege et al. (2009) connect the CDS auction mechanism and outcomes with corporate bond prices and returns at default and just before recovery. Longstaff, Mithal, and Neis (2005) propose that CDS auction results are superior to bond prices at default as indicators of actual recovery rates because bond spreads are significantly more sensitive to illiquidity factors than CDS spreads. However, there are some arguments that the greater liquidity of the CDS market is not entirely passed on to CDS auctions, and both recovery rates may not accurately reflect actual recovery rates. Helwege et al. (2009) investigate if the recovery basis is large enough to "drive apart" the pricing of credit risk in the CDS market and secondary bond market. Using historical data, they determine that the estimates of recovery from CDS auction prices and the secondary bond market prices are close, suggesting little evidence of a large recovery basis. They also find little evidence that the illiquidity of the bond market affects how closely the bond market price "tracks" the auction price.

While Helwege et al. (2009) conclude that the bond price the day before or day of the auction is extremely close to the final recovery price in the CDS auction, they calculate several cases of abnormally high or low bond returns from the time of default to the auction day. In their paper, they do not investigate the source of these returns and/or volatility, and there is little other research examining the returns and return volatility of bonds from default to auction. The abnormality of these returns and return volatility around the time of default could indicate manipulation by market players, which this paper is the first to examine. This paper seeks to expand upon Helwege et al. (2009) by calculating bond return volatility around the time of default for a larger dataset of bonds both included in and not included in CDS auctions.

Although there is little research examining bond returns and volatility around the time of default, there is extensive research on corporate bond returns and volatility, return and volatility factors, and credit spreads. Significant research focuses on structural models of default; Jones, Mason, and Rosenfeld (1984) and Eom, Helwege, and Huang (2004) find that these structural models do not match the magnitudes of credit spreads. Specifically, Huang and Huang (2003) determine that numerous structural models underestimate corporate bond yield spreads when matched to historical default probabilities. This dislocation, named "the credit spread puzzle," has attracted significant research since Huang and Huang (2003). This research endeavors to explain the credit spread puzzle, particularly through model dynamics, see, for example, Elias, Hellwig, and Tsyvinski (2014), Bhar and Handzic (2008), and Feldhutter and Schaefer (2018). Alternative literature suggests an illiquidity component, such as in Bao and Pan (2013) and Chen, Lesmond, and Wei (2007).

Bao and Pan (2013) confirm excess volatility in corporate bond and CDS returns and run a series of regressions to determine the cause of this excess volatility. To determine excess bond volatility, they compare bond volatility from the Merton model implied volatility, calculated from an extension of the Merton (1974) model using stochastic interest rates with Treasury bond and equity return volatilities, with empirical volatility from monthly returns, calculated from the transaction size-weighted prices. Bessembinder et al. (2009) recommend calculating prices as transaction size-weighted average prices to minimize the impact of bid-ask spreads in prices. Edwards, Harris, and Piwowar (2007) and Bao, Pan, and Wang (2011) further expand this research, showing high, negative autocovariance in the corporate bond market, suggestive of a large effective bid-ask spread which would dominate volatilities over short horizons and small trades. Bao and Pan (2013) determine that empirical volatility of credit securities is higher than Merton model implied volatility due to illiquidity rather than firm fundamentals. Consistent with Collin-

Dufresne, Goldstein, and Martin (2001) and Schaefer and Strebulaev (2008), Bao and Pan (2013) confirm both that the Merton model offers good estimates of fundamentals in the equity and corporate bond markets and that there are still some factors of debt returns and credit spreads that remain uncaptured in the Merton model.

The regression analysis and control variables used in this paper are primarily motivated by Bao and Pan (2013), as well as the aforementioned papers. This paper extends the work of Bao and Pan (2013) by examining empirical bond return volatility specifically around the time of default. It will also be the first to compare these metrics for bonds included in CDS auction and bonds that are not included and determine if there is indirect evidence of market participants manipulating bond returns and CDS for more favorable CDS auction outcomes.

3. News Review

While there is no previous research on determining empirical evidence of such manipulation, there has been significant media coverage, conversation, and debate about whether these events constitute market manipulation (Bloomberg, WSJ, Reuters). Perhaps the most topical case is the US homebuilder Hovnanian Enterprises Inc. trade in January 2018. Blackstone Group's credit hedge fund unit, GSO Capital Partners, offered Hovnanian a low-cost loan with the condition that Hovnanian default on a portion of its debt and issue weird new bonds to trigger the CDS and generate a large payout on the $300 million CDS position held by GSO.[7] These weird bonds offered very low coupons which

[7] Levine, Matt, 2018, "When Cleverness Becomes Manipulation," *Bloomberg*, *Apr* 26.

made the bonds extremely cheap and would maximize CDS payouts. Hovnanian agreed to default on a portion of its debt by missing a bond payment, known as a "manufactured default." Hovnanian was not in default, but GSO's loan rate was significantly cheaper and therefore more attractive than others' offers. Goldman, one of the CDS sellers on the trade, tried to push up the bond price to reduce its CDS payout. After another CDS seller, Solus Asset Management, tried to sue GSO, GSO altered its offer so that Hovnanian no longer had to default on a portion of its debt. Hovnanian paid the interest it had skipped and thus did not trigger the CDS payout.

Although GSO was not able to accomplish its manufactured default trade with Hovnanian, the hedge fund conducted a similar trade in 2013 with Spanish gaming company Codere. GSO offered a loan to Codere, structured in a way that would result in a payout on the CDS GSO held. The loan required Codere to pay an interest payment two days late, triggering the CDS "failure to pay" clause. Codere was willing to take the loan to ease its restructuring debate with bondholders, since many bondholders would gain from the CDS they simultaneously held. This "failure-to-pay" manufactured credit event resulted in a $197 million payment to holders of the CDS.[8]

GSO's manufactured credit events are only the tip of the iceberg as Sujeet Indap at the Financial Times writes, "US companies are facing an escalating threat from activist debt investors, who want to push them into default to make a profit from bearish bets on their bonds."[9] Codere is often regarded as the "precursor to iHeart," since the

[8] Ruhle, Stephanie, Mary Childs, and Julie Miecamp, 2013, "Blackstone Unit Wins in No-Lose Codere Trade: Corporate Finance," *Bloomberg*, Oct 23.
[9] Indap, Sujeet, 2018, "USA Inc Faces Growing Threat from Activist Debt Investors," *Financial Times*, Sept 18.

iHeartCommunications, Inc. case triggered the same "failure-to-pay" clause. iHeart chose not to repay the $57.1 million of principal on its 2016 senior unsecured notes held by its own affiliate but repaid the $192.9 million of principal on the same note held by outside investors. While some of these cases offer a benefit to the company defaulting, other more severe cases do not. For example, at the end of 2017, Aurelius Capital Management, who held a significant bond and CDS position in Windstream, began a legal case arguing the company had been in default for two years to trigger profits from its CDS position. As these cases increase in frequency and severity, concern is rising that more and more financial institutions will follow GSO, Aurelius, etc., in performing this "net-short debt activism."

Hedge funds have also manipulated the CDS market in the opposite direction, in which a hedge fund offers a distressed company a deal that helps keep the company afloat and prevents triggering the CDS payout. Bolton and Oehmke (2009) investigate the classification of these restructuring deals and their effect on CDS contract prices, creditor behavior, and credit market outcomes. They determine that, while classifying debt restructuring as a credit event reduces restructuring inefficiencies that result from the empty creditor problem, it also eliminates the economic gains from the use of CDS as a commitment device. Both Amherst Holdings in 2009 and Radioshack's CDS writers in 2014 similarly sold CDS and used the proceeds to buy up the company's bonds or offer a cheap loan to prevent default, a form of restructuring.

ESL Investment Inc. and Chatham Asset Management designed more creative engineered credit events in May and April of 2018, respectively. ESL, the biggest Sears shareholder at the time, offered to buy some of Sears' businesses in exchange for Sears buying back a portion of its own lower priced debt, resulting in large profits for CDS writers that were betting on Sears staying afloat for the next year.[10] Chatham offered to refinance most of McClatchy's debt with two new loans under one of its subsidiaries, creating what is termed an "orphaned contract" for its CDS because CDS holders would hold insurance on an entity without significant debt. If the deal had gone through, Chatham, who had been selling CDS and buying up the underlying bonds to raise prices, would be the seller of insurance against a nearly impossible default because of the lack of debt. The two new loans would also be sold to Chatham at a premium to par because of its own buying of McClatchy's bonds. [11]

All of these engineered credit event cases are one of two scenarios: (1) buying CDS (long protection, short credit) and triggering the CDS clause or (2) selling CDS (short protection, long credit) and preventing default. Both scenarios represent potential manipulation in the credit derivatives market. The CFTC has voiced their opinion, stating "intentional defaults, which are not tied to a company's financial health, could amount to 'market manipulation' and 'severely damage' the CDS market."[12] The ISDA board also published a statement in April, "we believe that narrowly tailored defaults, those that are designed to result in CDS payments that do not reflect the creditworthiness of the underlying corporate borrower, could negatively impact the efficiency, reliability, and fairness of the overall CDS market."[13] Thus, these CDS and bond price manipulations,

[10] Boston, Claire, and Sridhar Natarajan, 2018, "Sears Looks Like the Next Company With a Head-Scratching CDS Trade," *Bloomberg*, May 22.
[11]Natarajan, Sridhar, 2018, "This Hedge Fund Trade Is Stirring Fresh Controversy in the CDS Market," *Bloomberg*, Apr 2013.
[12] Scigliuzzo, Davide, 2018, "CFTC Steps into Debate on Voluntary Defaults," *Thomson Reuters*, Apr 27.
[13] Internatinoal Swaps and Derivatives Association, Inc., 2018, "ISDA Board Statement on Narrowly Tailored Credit Events," Apr 11.

many of which are unexposed, are an ongoing problem that future regulation may or may not be able to address.

4. Overview of CDS Auction Design

CDS auctions determine the payments by CDS sellers to CDS buyers after the default of bonds. Auctions are used to settle CDS trades of defaulting firms to improve settlement efficiency and determine a uniform recovery price for the underlying debt, minimizing "recovery basis risk," which would otherwise occur if the recovery were not the same for all instruments. Investors have the option of cash settlement or effectively physical settlement because bonds can be traded in the auction. All CDS trades in the auction are cash settled, where in the physical settlement option a CDS buyer receives the principal balance outstanding (par in this case) from the trading of the underlying cash obligation (Creditex and Markit (2010)). For example, if there is a 30% recovery rate, the CDS buyer receives 70% of par.

Because of the requirement to settle in cash with an option to effectively physically settle, CDS auctions are an unusual two-stage process (Helwege et al. (2009)). In the first stage of CDS auctions, dealers provide a two-way quote for the defaulted assets and physical settlement requests are made (requests to buy or sell deliverable obligations at the final price). The dealers' quotes are used to determine the initial market midpoint and the physical settlement requests are summed to measure open interest, which is used in the second stage.

The initial market midpoint, size and direction of open interest, and adjustment amounts are published on Creditfixing's website within 30 minutes. Then, dealers and investors have 2-3 hours to decide if they would like to place limit orders on the deliverable obligations (and if so at what level) in the second stage of the auction. The initial market submissions on the relevant side are used as limit orders in the second stage of the auction as well. Limit order bids/offers are bound by the "cap," usually half of the bid-offer spread. Further, if the open interest is to buy, a limit offer's lower bound is the initial market midpoint minus the cap (any offers below are bumped to this value). If the open interest is to sell, a limit bid's upper bound is the initial market midpoint plus the cap (any bids above are knocked to this value).

Next, if the open interest is to buy/sell, the lowest/highest 'sell'/'buy' limit order is matched with the open interest that is equal in size. The next lowest/highest order is then matched, and the process continues until all open interest has been matched, in which the last match is the final price. If all limit orders are matched first, the final price is par if open interest is to buy and zero if open interest is to sell. Further, if the final limit order is greater than the initial market midpoint plus the cap or less than the initial market minus the cap, the final price will be the initial market midpoint plus or minus the cap, respectively (Creditex and Markit (2010)).

Although Chernov, Gorbenko, and Makarov (2013) and Du and Zhu (2016) demonstrate that there is not a huge amount of bias in the final auction price, they ignore market participants' activity in the bond market before default and even between default and auction. In the current CDS auction design, participants in the first stage influence the quantity of bonds to be auctioned (the open interest) in the second stage of the auction, therefore influencing the final price. Because dealers' markets create the initial market midpoint, dealers can influence the upper/lower bounds for pricing limit orders and the final auction price as well. Second stage participants (those placing limit orders) may hold derivatives on the assets being auctioned and thus, CDS auction participants may have large incentives to manipulate prices to gain from their existing positions, a major bias inherent in the current structure of CDS auctions.

Specifically, a company's lowest-priced debt is typically used to determine credit derivative payouts, and so when an institution bids up the bond price (Chatham/McClatchy and Goldman/Hovnanian) or takes out the lowest-priced debt (ESL/Sears), it dramatically reduces the CDS payout in the event of default. On the other hand, if a hedge fund owned a large CDS position, it would desire the bond price to decrease so it would receive a larger CDS payout after auction. This hedge fund could submit a large market sell order in the first stage of the auction and, depending on other market participants' orders, possibly cause the net open interest to be selling and favorably move the CDS payout. But, the extent to which participants can bid or ask for bonds in the first stage of the auction is limited by their CDS position size, so participants cannot submit an order to sell a large amount if they only hold a small CDS position. However, CDS auction outcomes are also partly determined by how much these bonds trade before auction. Therefore, pre-default and pre-auction bond manipulation could be an extremely effective tactic for market participants in order to achieve favorable CDS auction outcomes.

Collectively, CGM, (2013), GS (2011), Peivandi (2015), and DZ (2016) demonstrate that the current design of CDS auctions can lead to biased prices and inefficient allocations. CGM (2013) propose altering current auctions with the introduction of a pro-rata allocation rule and a conditional price cap to minimize mispricing. DZ (2016) also propose a method to improve current CDS auctions, although they recognize it is not the optimal method in practice. DZ (2016) recommend an alternative double auction design (as opposed to the current one-sided design) that would offer more efficient price discovery and allocations.

5. Data

5.1 Data Collection and Sources

To analyze corporate bond return volatility around default, I first use data from Moody's Default & Recovery Database (DRD). Moody's Investor Service uses DRD's issuer, default, and recovery data as the basis of their default research, which is used globally. This dataset is ideal for my purposes because it provides detailed coverage of default and recovery data for debts and corporate entities. I use this dataset to identify defaulted entities and issuances from 2005 to 2018 and define this as my defaulted bonds dataset. Each defaulted entity is dated by Moody's rating agency default date. For each entity, DRD provides the entity's industry, a default description blurb, the type of default, and resolution (if applicable). From DRD, it can be determined on which issuances each entity defaulted, the issuance-specific default date, and bond issuance characteristics, such as seniority, coupon, market, prior year's rating, and default price where applicable.

Next, I use Markit CDS data to determine which entities have CDS traded. This dataset consists of currently or historically traded CDS and provides the corresponding entity CUSIP, redcode, ticker, reference entity, jurisdiction, etc. I use this dataset as a reference for which bonds have reference entities that currently have or previously have had CDS trading. To determine which bonds are included in CDS auctions at the time of the bond and reference entity's default, I use Creditfixings and ISDA's CDS Index Protocols to identify CDS auction data. For each defaulted entity with auctionable CDS, the Protocol provides market participants with a method to address the settlement issues on the entity's credit derivative products through the CDS auction process.

The Protocol identifies each deliverable obligation to be priced and settled in the auction. The details of this auction settlement process, dealer bid/offers, initial market midpoint, net open interest, and final auction price are publicly available from the Creditfixings website. I construct my own CDS auction dataset consisting of each auction's deliverable obligations. I then add all senior (unsecured and non-subordinated) deliverable bonds in my CDS auction dataset to my defaulted bonds dataset that are not already included in the latter. Although these additional bonds are not necessarily in default, they are subject to the same possible price manipulation around the time of the issuer's default because of their inclusion in CDS auction.

The bond pricing data for the defaulted and deliverable bonds in this paper are acquired from FINRA's TRACE (Transaction Reporting and Compliance Engine). This dataset exists because of regulatory changes that aimed to add greater transparency in corporate bond markets. FINRA, successor to the NASD, regulates trading in equities, corporate bonds, securities, and options and reports OTC corporate trades. This dataset is optimal for my purposes because it provides "time-stamped" trading activity containing the clean price and par value traded which I use to calculate daily bond returns and volatility as well as several bond illiquidity measures. However, the par value traded is capped at $1 million+ for speculative great bonds and $5 million+ for investment grade bonds.[14] Nearly all of the bonds in my sample defaulted after the NASD implemented Phase III of bond transaction reporting on February 7, 2005, which expanded reporting requirements to approximately 99% of total U.S. corporate bond market activity in over 30,000 securities.

I match my defaulted bonds dataset, which includes bond characteristics from DRD, with the bond pricing data from TRACE. The DRD bond characteristics data is crosschecked with Bloomberg Historical Data, and I fill in missing values where applicable, namely for deliverable obligations from CDS auctions.[15] DRD also provides the default date, which determines the dates of my trading time periods for each issuance. For each of the deliverable obligations added from CDS auctions, I use the default date for its issuer.

The remaining data is from standard sources – firm fundamental data is from Compustat and bid-ask spreads are from Bloomberg Historical Data.

5.2 Data Description

The bond data is restricted to bonds that have defaulted between January 1st, 2005 and August 31, 2018 because Creditfixings began publishing auction settlement data beginning in 2005.[16] As motivated by Bao and Pan (2013), the bond sample is reduced due to the exclusion of all non-regular bonds and Financials, which make up about one-third of my dataset. [17] The bond data is further restricted by TRACE's coverage, which includes corporate bond trades for U.S. companies only. Similar to most studies using bond pricing

[14] Par value traded is top-coded at $5 million for investment grade bonds and $1 million for speculative grade bonds.
[15] I do not use FISD as in previous literature because of lack of access to the database.
[16] August 31, 2018 being the start date of this research and therefore when the data was downloaded.
[17] Moody's classifies a regular bond as one with no special features or hybrid characteristics.

data from TRACE, such as Bao and Pan (2013), Dick-Nielsen, Feldhutter, and Lando (2012), and Helwege et. Al (2009), my sample is also limited because many bonds do not trade frequently. Lastly, I drop bonds issued by entities with insufficient information in Compustat for firm-level data and bonds that are missing other metrics, such as rating, bid-ask spread, etc., around the time of default. For my longest time period, from 12 months before default to 29 days after default, these restrictions reduce my sample to 609 bonds that traded within the time period and 335 bonds that have data for each metric.[18] The sample size decreases slightly in smaller time periods around default due to some bonds' lack of trading. The smallest sample size is during the time period from default to 29 days after default, in which there are 554 bonds that traded and 247 bonds that have data for each metric.

5.3 Return Construction

I use the transaction-level bond pricing data from TRACE to construct bond return volatility for the bonds in my sample. As shown in Table 1, I examine 5 different time periods: 12 months before default to 29 days after default (12BDEFA), 12 months before default to default (12BDEF), 6 months before default to 29 days after default (6BDEFA), 6 months before default to default (6BDEF), and default to 29 days after default. Twenty-nine days after default is chosen because that is the approximate time between default and auction for the bonds in my sample.[19]

[18] TRACE and Compustat differ on many entity CUSIPs. As such, most Compustat identification keys are determined manually (by looking up the name) for each entity. There are several entities that Compustat does not contain, and thus these are either omitted or included under their parent organization, where applicable.
[19] I determine this number by calculating the mean and median for time from default to auction for firms in my sample, while eliminating outliers.

First, I construct daily bond returns as follows. For a bond on day t, I take all trades from that day and calculate the clean price for the day as the transaction size-weighted average price of these trades. By transaction-size weighting prices, I minimize the effect of bid-ask spreads in prices.[20] Returns are then constructed as:

$$R_t = ln\left(\frac{P_t + AI_t + C_t}{P_{t-1} + AI_{t-1}}\right) \quad (1)$$

where P_t is the transaction size-weighted average clean price, AI_t is the accrued interest, and C_t is the coupon paid on day t. This method of calculating bond returns is motivated by Bao and Pan (2013), but I calculate daily returns rather than monthly returns because of my narrow time periods and the large and rapid price moves of bonds around default.[21] Coupon rates and maturities are determined by DRD and Bloomberg. Accrued interest is calculated daily using the standard 30/360 convention, where applicable. Given the riskiness of many of the bonds in my sample and the nature of trading around default, it is unsurprising that there are days in the time periods that some bonds do not trade. I treat bond returns as independently and identically distributed (i.i.d.). This allows me to create

[20] Bessembinder, Kahle, Maxwell, and Xu (2009) advocate calculating prices as the transaction-size weighted average of prices to minimize the effects of bid-ask spreads in prices. Edwards, Harris, and Piwowar (2007) and Bao, Pan, and Wang (2011) show that these effects are greatest for small trades. I calculate transaction-size weighted clean prices by weighting each trade's clean price by its volume and taking a daily average of all trades.

[21] Bao and Pan (2013) calculate monthly returns using a transaction-size weighed average of all trades from the 21st of the month or later. This allows for a balance between prices that reflect month-end prices and a reasonable number of trades to calculate average prices.

standardized daily returns, even if there are several days between trades in a given time period.[22] I then calculate the volatility of daily returns for each time period and annualize.

5.4 Bond Illiquidity Proxy Construction

At the bond level, I construct a series of illiquidity variables. Dick-Nielsen, Feldhutter, and Lando (2012) note that there is no clear consensus on how to assess the illiquidity of an asset, and so I analyze a number of illiquidity-related measures for corporate bonds according to the previous literature.[23] First, I include age and amount outstanding of a bond as motivated by Houweling, Mentink, and Vorst (2005).[24] Following Chen, Lesmond, and Wei (2007), I collect bid-ask quotes from Bloomberg, but pull daily quotes rather than quarterly because I use daily returns to calculate volatility.[25] For each day, I calculate the daily spread as:

$$B/A\ Spread = \frac{Ask - Bid}{MidPrice} \quad , \quad MidPrice = \frac{Ask + Bid}{2}$$

Because there are not always bid-ask quotes every day, I take the monthly average in order to include as many bonds as possible. I define the B/A Spread for each time period as the mean monthly average over the time period. Following Bao and Pan (2013), I introduce

[22] By assuming i.i.d., I can calculate the return between trades ("trade to trade return") when there are several nontrading days between trades. I divide the trade to trade return by the number of days between trades to determine the standardized daily return.
[23] See Bao and Pan (2013), Dick-Nielsen, Feldhutter, and Lando (2012), Houweling, Mentink, and Vorst (2005), Chen, Lesmond, and Wei (2007) for discussion. Chen, Lesmond, and Wei (2007) also note the tradeoffs to using each measure while employing each measure to determine the relation between corporate bond yield spreads and liquidity. This both increases robustness and illustrates the comparative power of each metric.
[24] See Houweling, Mentink, and Vorst (2005) for further discussion.
[25] The bid-ask quotes from Bloomberg are the Bloomberg Generic Quote, which reflects the consensus quote among market participants.

the standard deviation of the bid-ask spread to account for the possibility of changing illiquidity during the time periods.

As in Dick-Nielsen, Feldhutter, and Lando (2012), I include bond zero, calculated as the percentage of days in the time period for which the bond did not trade.[26] I also include the four core illiquidity metrics used in Dick-Nielsen, Feldhutter, and Lando (2012): the Amihud illiquidity measure, the volatility of the Amihud measure, the Implied Round Trip Cost (IRC), and the volatility of the IRC. All four measures are calculated using the TRACE bond pricing data. The Amihud (2002) measure, defined as the price impact of a trade per unit traded, calculates the price impact of trades. The measure is constructed as the daily average of absolute returns r_j divided by the trade size Q_j of consecutive transactions:

$$Amihud_t = \frac{1}{N}\sum_{j=1}^{N_t}\frac{r_j}{Q_j} = \frac{1}{N}\sum_{j=1}^{N_t}\frac{\left|\frac{P_j - P_{j-1}}{P_{j-1}}\right|}{Q_j},$$

where N_t is the number of returns on day t.[27] I then define the Amihud measure as the mean of daily measures for each time period and include the standard deviation measured over the time period as the volatility of the Amihud measure. The IRC is a proxy for bid-ask spreads, hinged on finding two or three trades very close in time that are likely a result of a dealer matching a buyer and a seller and taking the bid-ask spread as a fee. If there are two or three trades of the same size on a bond on the same day and no other trades of

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[26] Dick-Nielsen, Feldhutter, and Lando (2012) refer to this measure as bond zero-trading days.

[27] In Dick-Nielsen, Feldhutter, and Lando (2012), at least two consecutive transactions on a given day are required to construct the Amihud measure. In order to include as many bonds as possible because there are several days that bonds do not trade, I loop to the previous trade and divide by the days between, as in my return construction, to calculate the average daily Amihud rather than using only consecutive trades on the same day.

the same size occur on that day, I consider the trades as part of an Imputed Roundtrip Trade (IRT). I then calculate the IRC as:

$$IRC = \frac{P_{max} - P_{min}}{P_{max}},$$

where P_{max} is the largest price in the IRT and P_{min} is the smallest price. Since the IRC could depend on trade size, I construct daily IRC values as the average roundtrip costs for all trade sizes on that day. I define the IRC as the mean of daily measures for each time period and introduce the standard deviation measured over the time period as the volatility of the IRC.[28]

5.5 Firm Fundamentals Construction

At the firm level, I construct a series of variables as proxies for firm fundamentals. I include EBIT/Assets, Sales/Assets, and Retained Earnings (RE)/Assets due to their inclusion in the Altman (1968) Z-Score as metrics to predict bankruptcy. This is particularly important since my dataset consists of defaulted firms at risk for bankruptcy. I introduce a leverage ratio, defined as Total Debt/Assets, to reflect the credit risk of the firm and the Coverage Ratio to measure the ability of a firm to pay interest expenses with earnings (Blume, Lim, and MacKinley (1998)).[29] I also include Net Income/Assets and log(Assets), as motivated by the logit default predication model in Campbell, Hilscher, and Szilagyi (2008) and the tendency for firms with CDS to be larger in size (Subrahmanyam,

[28] It is likely investors are concerned with future bond liquidity levels as well as the current level. The volatility of the Amihud measure and IRC thus may affect liquidity spreads and bond return volatility as noted in Dick-Nielsen, Feldhutter, and Lando (2012).
[29] I define Coverage Ratio as operating income after depreciation plus interest and related expense divided by interest and related expense.

Tang, Wang (2014), Batta and Yu (2017)). These level firm fundamentals are calculated from Compustat at dates closest to but not less than 30 days before each firm's default.

In addition to these level variables, I include four variables to account for the volatility of firm fundamentals. I calculate the volatility of Cash Flow/Assets following Minton and Schrand (1999) and volatility of Earnings/Assets following Jayaraman (2008). I also include the leverage (Total Debt/Assets) volatility, as motivated by Collin-Dufresne and Goldstein (2001), and sales (Sales/Assets) volatility, as motivated by Sufi (2009). I construct all of these firm fundamental volatility variables using quarterly Compustat data for the five years prior to each firm's default. The inclusion of RE/Assets, EBIT/Assets, leverage, log(Assets), and these other firm fundamental proxies is further motivated by their influence on the propensity of a firm to have CDS trading and therefore a CDS auction (Subrahmanyam, Tang, Wang (2014)). These variables may also reflect a firms' credit risk and thus market participants' demand for CDS to hedge (Batta and Yu (2017)).

5.6 Sample Description

Table 2 summarizes the corporate bonds in my sample for the largest most comprehensive time period, 12BDEFA. The summary statistics for the remaining time periods are shown in the Appendix in Tables A1-A4. As shown in Table 2, 12BDEFA includes 609 bonds, largely reduced due to the limitations as explained in Section 4. There are 373 bonds not in CDS auction and 236 bonds that are in CDS auction, thus 38.8% of bonds in my sample are in CDS auction.

As shown in Panel A, the sample has an average amount outstanding of $400 million. Neither the average amount outstanding nor the average rating differ significantly between Panel B, bonds not in CDS auction, and Panel C, bonds in CDS auction. The average rating is 17.15 (17 = Caa1) and the average age is 5.84 years. Bonds in CDS auction are both notably older and have a longer time until maturity than bonds not in CDS auction, with an average age of 7.28 years vs. 4.96 years and an average time until maturity of 5.275 years vs. 6.351 years. There is also a larger average amount of trading on bonds in CDS auction than those that are not, both by number of trades (2,309 vs. 1,692) and volume traded (803.5 million vs. 507.5 million). Furthermore, bonds in CDS auction have higher Amihud and IRC measures than bonds not in CDS auction, with values of 0.00894 and 0.00572 for the Amihud measure and 2.139 and 1.625 for the IRC measure. The same relationship is true for the standard deviation of these variables. The B/A Spread is slightly lower for bonds in CDS auction than bonds not in CDS auction (3.012 vs. 3.138). These differences suggest that, although bonds in CDS auction have a higher number of trades and volume of trading, bonds in CDS auction may be less illiquid than bonds not in CDS auction.

Table 2 also shows that, with the exception of Sales/Assets, the average firm-level fundamental ratios are negative. This is intuitive given that these firms are about to enter default when these metrics are calculated. However, these ratios are either less negative or positive for bonds not in CDS auction. For bonds in CDS auction, these ratios are more negative, suggesting that firms with bonds in CDS auctions may be in greater financial distress. This result is intuitive since riskier firms are more likely both to be in greater financial distress and to have bonds outstanding with CDS written on them and therefore a CDS auction.

The remainder of this paper formally analyzes the aforementioned patterns by examining the effect of CDS auction on bond return volatility while controlling for bond characteristics, illiquidity, and firm fundamentals.

6. Methodology

To investigate bond price manipulation around default, I examine the effect of bonds' inclusion in CDS auctions on bond return volatility for time periods around default. I begin with the following baseline regression specification:

$$\sigma_i = \gamma CDSAuction_i + \beta_1{}' b_i + \beta_2{}' liq_i + \beta_3{}' f_i + \varepsilon_i \qquad (2)$$

where σ_i represents the bond return volatility for bond i. The variable of interest, $CDSAuction_i$, equals one if the bond is a deliverable obligation in an entity's CDS auction and zero otherwise. Among the included control variables, b_i denotes bond-level controls that are not included in illiquidity (Moody's rating, and time to maturity), liq_i bond-level illiquidity control variables (age, amount outstanding, B/A spread, standard deviation of B/A spread, bond zero, Amihud, standard deviation of Amhiud, IRC, and standard deviation of IRC), f_i firm-level fundamental control variables (EBIT/Assets, Coverage Ratio, Sales/Assets, RE/Assets, NI/Assets, leverage, log(Assets), cash flow volatility, earning volatility, sales volatility, and leverage volatility), and e_i the residual term.

Under the assumption that CDS auction is exogenous to the dependent variable, σ, the projection coefficient γ, identifies the treatment effect, without any control variables. However, if having CDS auction is endogenous, γ cannot be identified. Since random assignment of a CDS auction is likely implausible, I include a large number of control variables related to firm fundamentals, bond-level metrics, bond illiquidity, and CDS auction propensity. The identifying assumption underlying my empirical strategy is that CDS auctions are randomly assigned, conditional on my controls. Any unobserved factors that influence both CDS auction assignment and bond volatility will bias my estimates of the treatment effect. I calculate both heteroscedasticity-robust standard errors and clustered standard errors by distinct default event.

First, I examine the relation between bond return volatility, the CDS auction indicator, and variables that proxy for bond-level controls, firm-level fundamentals, and bond illiquidity around the time of default, using the baseline regression shown in Equation 2. I look at five time periods, defined in Table 1, to determine whether the significance and impact of certain variables change in differing time periods around default, namely, in a longer/shorter time period before default and the time period after default. If bond price manipulation, indirectly represented by bond return volatility, is present around the time of default, the $CDSAuction_i$ variable of interest should be significant and positive, based on the assumption that manipulated bonds and derivatives experience greater bond trading and price volatility around the time of default as market participants attempt to move prices favorably for more profitable auction outcomes.

Second, to demonstrate the robustness of my treatment effect estimate, I use propensity score matching (PSM) to identify control bonds not included in CDS auction that have a similar likelihood of "treatment," or inclusion in CDS auction, as CDS auction bonds do. The matched sample is then used to run the same baseline regression. This requires the same identification assumption as the baseline regression model above - random assignment of CDS auctions, conditional on my covariates. This assumption implies random assignment of CDS auctions, conditional on the probability of treatment, where the probability of treatment is determined by my covariates. A key advantage of PSM is that it avoids functional form specification for treatment, and thus does not depend on an evident source of exogenous variation for identification.[30] It can therefore be used to reduce or eliminate the effects of confounding when estimating treatment effects. Further, by creating a matched sample, PSM addresses the differences between the CDS auction sample and the non-CDS auction sample that may not be properly or fully controlled for with a linear specification, provided the potential outcome is independent of treatment, conditional on the propensity score that is determined by my covariates. Further, another key advantage of PSM is that, assuming CIA, it can estimate treatment effects, particularly the ATE, while regression estimates the weighted ATE (WATE), where weighting is by the variance of treatment.

Then, I implement double-robust estimators, which combine the outcome volatility regression with a model for the treatment to estimate the causal effect of a treatment on an outcome. In this paper, the treatment is a bond's inclusion in CDS auction and the outcome is bond return volatility. Bang and Robins (2005), Robins, Rotnitzky, and Zhao (1994), and Robins (2005) introduced these estimators as unbiased estimates of the treatment effect when only one or both of these models are correctly specified, while still assuming there are no unmeasured confounders. However, prior simulations have proven that the double-robust estimator is unbiased if a confounder is omitted from one, but not both, of the component models (Robins (2005), Davidian (2004)). Funk (2008) confirms this and

[30] See Rosenbaum and Rubin (1983), Rosenbaum and Rubin (1984), Austin and Mamdani (2006), Imbens (2004), Subrahmanyam, Tang, Wang (2014) for further discussion on propensity score methods.

expands its validity to when one of the two models has been misspecified by categorizing a continuous confounder.

Lastly, I run my baseline regression (Equation 2) with time fixed-effects, first with heteroscedasticity-robust standard errors and then with standard errors clustered by distinct default event. I examine time fixed-effects using both quarterly time periods (year-quarters) and yearly time periods (years). CDS auction defaults could tend to occur during periods of high market volatility. If so, some of the volatility effects attributed to CDS auction in the baseline regression should be attributed to higher market volatility. Running the baseline regression with time fixed-effects controls for any time-varying cross-sectionally-invariant variations in bond return volatility that are potentially omitted from my baseline regression. However, it also could be that CDS auction defaults tend to happen during periods of high market volatility because market participants' battling for favorable positions and CDS auction outcomes around the time of default increases market volatility. In addition, all the bonds in my sample are defaulted bonds or CDS auction bonds, so there is still the control in my first baseline regression that all bonds are analyzed at a similar moment in time, respectively, the time of each bond's default.

7. Empirical Results

7.1 Baseline Regressions

I begin my analysis of bond return volatility, which represents indirect evidence of bond price manipulation, around default using the cross-sectional volatility regression setup shown in Equation 1 for different time periods, as outlined in Section 6. I regress bond return volatility on my variable of interest, CDS Auction, and proxies for firm fundamentals and illiquidity as well as the volatility of fundamentals and illiquidity. The results are presented in Tables 4-9. Rating and time until maturity are included as bond-level controls for all specifications.

As shown in Table 2, the sample of DEFA consisted of fewer bonds and a lower average number of trades. Because of the smaller sample size of DEFA, I also look at time periods of post-default combined with pre-default (12BDEFA and 6BEFA) to jointly analyze bond return volatility before and after default. Further, except for the specification 9, I omit the controls that are highly correlated with another variable in the regression.[31] The correlation matrix of these variables are shown in Table 3. The omitted controls are the standard deviations of the B/A Spread, Amihud, IRC, and leverage because they are highly correlated with the B/A Spread, Amihud, IRC, and leverage, respectively, and Net Income/Assets and Coverage Ratio, because they are both highly correlated with EBIT/Assets.

Across nearly all specifications for all time periods, I find evidence of a positive relation between bond return volatility and CDS auction at the 10 percent significance level. In some specifications for certain time periods, I find significance at the 1 percent level. In specification 10, in which I two-way cluster standard errors by distinct default event, CDS auction is not significant at the 10 percent level. However, there is a "small sample problem" that arises when clustering with small and narrowly defined samples like my dataset. Further, under my identification assumption that CDS auction is randomly

[31] High correlation is defined as greater than 0.75 in this paper.

assigned, conditional on my controls, clustering is not necessary. Thus, it is unsurprising that I lose some significance of my CDS auction coefficient and most other variables.[32] Nonetheless, the coefficient on CDS auction is always positive and generally significant at conventional levels and varies from 0.249 to 1.357 across specifications and time periods. Bond return volatility around default is therefore likely much higher as a result of a bond's inclusion in a CDS auction. The average annual bond return volatility across all bonds around the time of default is 99.6% to 139.8% and a bond that is included in a CDS auction is associated with greater bond return volatility of 24.9 to 135.7 percentage points around default than a bond not included in a CDS auction. While this is a wide range, the range is unsurprising given firms' financial distress, market participants' erratic trading, and possible manipulation of bond prices around the time of default.

Looking at other variables in the regressions, bond zero is significantly positively related to volatility in all specifications at the 1 percent significance level except in specification 10 and time period DEFA. This suggests that the fewer the days that a bond trades in a time period, the greater the bond return volatility. Consistent with previous literature on bond return volatility and illiquidity (Bao and Pan (2013)), the IRC is significantly positively related to volatility in nearly every specification and time period, and the Amihud is as well in time periods 12BDEFA, 12BDEF, and DEFA. However, the B/A Spread is positively related to volatility with statistical significance in limited specifications and time periods. It is reasonable to expect a positive significant relationship

[32] See Bakirov and Székely (2005), Ibragimov and Müller (2010), Imbens and Kolesar (2016), Ibragimov and Müller (2016), Abadie et. Al (2017) for discussion of small sample problem and clustering methodology.

between illiquidity measures and bond return volatility around the time of default since previous literature demonstrates that corporate bonds' yield spreads are related to proxies for illiquidity.[33]

Firm fundamentals, on the other hand, are seldom statistically significantly related to volatility. However, RE/Assets and Sales/Assets are significantly negatively related to volatility in many specifications and time periods. It follows that greater earnings and sales might decrease risk and therefore decrease bond return volatility. Further, cash flow volatility is statistically significant in time period DEFA, suggesting that having a historically higher cash flow volatility might increase bond return volatility after default. Lastly, unlike in Bao and Pan (2013), in most specifications and time periods, rating is insignificantly related to volatility, except in time period DEFA. This suggests that the rating of the bond has a greater impact on bond return volatility after default than before default. The poorer the rating, the greater the bond return volatility, which is intuitive since a bond with a lower rating is riskier and thus more likely to experience greater bond return volatility after default as market participants may strive for favorable auction pricing and/or default outcome. It could also be that the poorer the rating the more uncertainty there is regarding the default outcome and possible default resolution. Lastly, time until maturity is significantly negatively related to volatility.

I now focus on specification 8 across time periods, presented in Table 4. In this specification, I omit the controls that are highly correlated with another variable in the regression, but include all other controls and my variable of interest. CDS auction is

[33] See Chen, Lesmond, and Wei (2007), Bao, Pan, and Wang (2011), Dick-Nielsen, Feldhutter, and Lando (2012), and Friewald, Jankowitsch, and Subrahmanyam (2012) among others.

statistically significant across all time periods. A bond that is included in a CDS auction is associated with a greater annual volatility of 31.2 to 63.8 percentage points. The coefficient on CDS auction is smallest for time period 12BDEF, and is greater for 12BDEFA when the post default time period is included. However, time period 6BDEF has the highest coefficient, higher than both time period 6BDEFA and DEFA. This suggests that there is greater bond return volatility for bonds included in a CDS auction in the six months before default than in the twelve months before default or in the post default time period. This indirectly supports the hypothesis that there is bond price manipulation for these CDS auction bonds around the time of default as market participants try to build up a favorable position prior to default, particularly in the 6 months prior. This manipulation is then continued, but possibly less intensely, after default due to the auction design and battle between market participants for favorable pricing during the auction settlement process.

Furthermore, Table 4 shows that illiquidity measures are of greater statistical significance than are firm fundamentals across time periods. However, there are more statistically significant illiquidity variables for 12BDEFA and 12BDEF than 6BEFA and 6BDEF. It could be that ordinarily these variables are significantly positively related to volatility. But when a company is on the verge of default and market participants may be trying to build favorable positions prior to an anticipated default, these illiquidity variables are of weaker significance and whether the bond will be included in a CDS auction is more significant and has a greater impact on volatility.

Surprisingly and unlike in previous literature, time until maturity is negatively related to volatility. This relation suggests that, around the time of default, bonds with greater time until maturity experience less price volatility. Time until maturity is statistically significant at the 1 percent or 5 percent levels in all time periods except for after default. In the post-default period, CDS Auction, Rating, B/A Spread, Amihud, IRC, and cash flow volatility are significantly positively related to volatility. These factors differ slightly from the significant factors in pre-default time periods. This result could be because of the small sample size and the short length of this time period or because different factors influence bond return volatility after default as a result of the auction design, battle among market participants for favorable pricing if there is an auction, and/or issuers and market participants' attempts to create the most advantageous default outcomes.

Overall, the baseline regressions clearly demonstrate the positive significance of CDS auction on bond return volatility around the time of default, as well as the positive relation between illiquidity measures and bond return volatility. This positive significance provides indirect evidence of bond price manipulation around default for bonds that are in CDS auction.

7.2 Propensity Score Matching

In this subsection, I repeat the previous baseline regressions (specification 8) using propensity score matched samples. The propensity scores are calculated with a probit model of CDS auction, as shown in Table 10. I use several of the variables included by Saretto and Tookes (2013) and Subrahmanyam, Tang, and Wang (2013) and add additional firm fundamental level and volatility variables. As in the baseline regressions, I exclude firm fundamentals that are highly correlated, namely Coverage Ratio, Net Income/Assets, and leverage volatility. I use two different matching criteria: (1) nearest neighbor, in which one non-CDS auction bond with the nearest propensity score is matched to each CDS auction bond and (2) three nearest neighbors, in which three non-CDS auction bonds with the closest propensity scores are matched to each CDS auction bond.[34] As the summary statistics in Table 2 demonstrate, CDS auction bonds and non-CDS auction bonds can be quite different in terms of age, illiquidity measures, and several firm fundamentals. The goal of PSM is to create a matched sample in which these differences are removed to be able to isolate the treatment effect of CDS auction.

Table 11 shows the average predictive effect on the treated and average predictive effect of CDS auction on bond return volatility using PSM, which can be interpreted as the average treatment effect on the treated (ATET or ATT) and average treatment effect (ATE), respectively, under my identification assumption. The ATET measures the expected causal effect of the treatment for those bonds in the treatment group, whereas the ATE measures the expected causal effect of the treatment across all bonds. The ATET and ATE are positive and significant at the 1 or 5 percent level across all time periods and matching criteria. More specifically, the estimated ATET of CDS auction on bond return volatility indicates that, depending on the time period around default, the average bond return volatility for a CDS auction bond is 75.4 to 157.5 percentage points higher than if it is not in a CDS auction. Further, the ATE of CDS auction on bond return volatility estimates that the bond return volatility around the time of default is 63.7 to 191.1 percentage points higher when a bond is included in a CDS auction. The ATET and ATE differ in magnitude slightly, which suggests that the treatment assignment, or whether a bond will be in a CDS auction, may not be random.

[34] Following Subrahmanyam, Tang, and Wang (2013) and Batta and Yu (2017) I use nearest neighbor matching. As in Subrahmanyam, Tang, and Wang (2013), I use nearest neighbor k matching but let k = 3 rather than 2.

To control for the possibility that treatment assignment may not be random and the potential lingering imbalances between groups, I replicate the analysis performed in Table 4 (Section 7.1) pertaining to the effect of CDS auction on bond return volatility around default. As shown in Table 12, CDS auction remains significantly positively related to bond return volatility in most time periods and matching criteria. In fact, with the exception of the time period DEFA, the CDS auction coefficients are mostly greater in magnitude and of greater significance than in Section 7.1.[35] With the matched sample, a bond that is included in a CDS auction is associated with a greater annual volatility of 26.2 to 114.0 percentage points. Consistent with Section 7.1 and Table 4, the coefficients on the 6 month before default time periods are the greatest, further supporting that there may be greater bond return volatility for bonds included in CDS auction in the 6 months before default than in the 12 months before default or in the time period after default. However, CDS auction is no longer significant for nearest neighbor and three nearest neighbors matching for the DEFA time period. This could be due to the lack of observations in the post default time period or inferior matching as a result of the short length of the time period, financial distress of the firm, and/or illiquidity of the bonds after default. Further, it could be that different factors influence bond return volatility after default due to the CDS auction design or the battle among issuers and investors for advantageous auction pricing or default outcomes.

As shown in Table 12, many of the control variables that are significant in the baseline regressions remain significant and of the same relative magnitude. However,

[35] 6BDEFA NN(3) is also an exception in which the CDS auction coefficient is smaller in magnitude and of less significance, but this may be due to the three nearest neighbor matching method because the coefficient in 6BDEFA NN(1) is greater in magnitude and of greater significance than in Section 7.1.

several factors are of greater significance and/or magnitude (log(Amt), Age, Amihud, IRC, Sales/Assets, RE/Assets) or are now significant (EBIT/Assets, log(Assets)). As in Section 7.1, illiquidity measures are of greater statistical significance across time periods than firm fundamentals. For the time periods 12BDEFA and 12BDEF, firm fundamentals are more significant and greater in magnitude than they were in the baseline regressions. This does not hold for the six month time periods, suggesting that firm fundamentals influence bond return volatility less the closer to default and, given the greater magnitude and significance of the CDS auction coefficient, whether a bond may be included in a CDS auction influences bond return volatility more.

Taken together, my previous findings that CDS auction is significantly positively related to bond return volatility around the time of default, particularly the six months prior to default, and that illiquidity measures are significantly positively related to bond return volatility, are robust to using a propensity score matched sample. The coefficient on CDS auction is greater in the PSM regressions than in the baseline regressions (0.262 to 1.140 vs 0.312 to 0.638). Similarly, for the illiquidity measures and few firm fundamentals that are significant, the coefficients from using PSM regression are generally higher than those from using baseline regression.

7.3 Double-Robust Estimators

Given the assumption of PSM that matching is based on observable information, I perform another robustness test by implementing double-robust estimators. The double-robust estimator is unbiased even if a confounder is omitted from one of the component models or when one of the models has been misspecified (Robins (2005), Davidian (2004), Funk (2008)). This doubly-robust method requires me to specify regression models for the outcome and the treatment as a function of covariates. I use the same baseline regressions as in Table 4 and treatment model as in Table 10 (Section 7.2), thus excluding highly correlated firm fundamentals in modeling treatment. I use two double-robust estimators through augmented inverse-probability weighting (AIPW) and inverse-probability-weighted regression adjustment (IPWRA), which both model the outcome and the treatment to account for the nonrandom treatment assignment.[36]

Table 13 shows the effect of CDS auction on bond return volatility using the AIPW and IPWRA double-robust estimators. I estimate the potential-outcome means, the ATE, and the ATET.[37] The average potential outcome for non-CDS auction bonds is always lower than the average potential outcome for CDS auction bonds. This difference further demonstrates that bonds included in CDS auction are associated with greater price volatility around default since the average potential outcome, or price volatility, is greater. Further, the ATET of CDS auction on bond return volatility indicates that, depending on the time period around default, the average bond return volatility for a CDS auction bond is 37.8 to 78.3 percentage points higher than if it is not in a CDS auction.[38] Further, the ATE of CDS auction on bond return volatility estimates that bond return volatility around the time of default is 14.6 to 75.7 percentage points higher when a bond is included in a CDS auction. The ATE values are significant for both estimators for 12BDEFA and

[36] As defined by Stata, RA estimators model the outcome to account for the nonrandom treatment assignment. IPW estimators model the treatment to account for the nonrandom treatment assignment. IPWRA uses IPW weights to estimate corrected regression coefficients that are then used to perform regression adjustment. The AIPW estimator adds a bias-correction term to the IPW estimator. If the treatment model is specified correctly, the bias-correction term is 0 and the model is reduced to the IPW estimator. If the treatment model is misspecified but the outcome model is specified correctly, the bias-correction term corrects the estimator. Both estimators are double-robust. https://blog.stata.com/2015/07/07/introduction-to-treatment-effects-in-stata-part-1/

[37] The potential-outcome mean is the average potential outcome for that treatment level.

[38] The ATET cannot be measured using the AIPW double-robust estimators.

12BDEF time periods and the AIPW estimator for 6BDEFA and 6BDEF time periods. These ATE values using double-robust estimators are smaller in magnitude than using propensity score matching as in Table 11.

However, these estimators have the double-robust property, which means that the estimates of the effects will still be consistent if the outcome or treatment model are misspecified or a confounder is omitted in one of the treatment models. Thus, the estimates suggest that CDS auction significantly positively impacts bond return volatility in the time periods twelve months and six months before default and when combined with the post default time period. As in Section 7.2, the double-robust estimators do not show CDS auction is significant for the time period DEFA. Therefore, my previous findings of the positive significance of CDS auction on bond return volatility for multiple time periods around default persist when using double-robust estimators. This positive significance when using double-robust estimators provides further indirect evidence of bond price manipulation around default for bonds that are in CDS auction.

7.4 Time Fixed-Effects

Because CDS auction bonds could have the tendency to default during high market volatility times, I first investigate the time distribution of default for CDS auction and non-CDS auction bonds. As shown in Figure 1, there does not seem to be a strong difference in the time distribution of default. However, I still run my baseline regressions (specification 8) with the addition of time fixed-effects by year-quarters and years to control for any time-varying cross-sectionally-invariant variations in bond return volatility that are potentially omitted from my baseline regression.

As shown in Table 14, the inferences in Section 7.1 are unchanged by the inclusion of time fixed-effects. The coefficients are of similar magnitude, although each coefficient is common to all year-quarters or years for the variable, respectively. Unlike in Section 7.1, the CDS auction coefficient for time period BDEFA with year-quarters time fixed-effects is significant at the 1 percent level and greater in magnitude (0.822 vs 0.383).[39] This suggests bonds in CDS auction experience significantly greater bond return volatility from time of default to auction, common to all year-quarters. As shown in Table 15, in which standard errors are clustered by distinct default event, the CDS auction coefficient for time period BDEF is also positively significantly related to bond return volatility, although slightly less significant. This relationship indicates indirect evidence of market participants manipulating bond prices after default leading up to CDS auction to achieve favorable positions and profitable CDS auction outcomes.

Table 15 also shows, however, that when using standard errors clustered by distinct default event, many of the CDS auction coefficients that were previously significant are no longer significant at the 10 percent level. Several other variables, such as Maturity, log(Amt), etc., are also no longer significant at the 10 percent level or are of less significance than they were in Section 7.1. The Amihud and IRC measures are still strongly significant in most time periods, further supporting the positive relationship between illiquidity measures and bond return volatility at the time of default.

Ultimately, by running time fixed-effects regressions, I am able to control for market-level variation that is not accounted for by my controls, although any omitted

[39] Although the coefficients in the time-fixed effects regressions represent the effect of CDS auction on bond return volatility within a given year. Or, put another way, the (weighted) average of the treatment effects that would be estimated if the regressions were ran separately each year.

factors that affect my cross-section of bonds differently are still threats to my identification of a treatment effect. I find CDS auction is positively significantly related to bond return volatility with time-fixed effects (Table 14), and positively related to bond return volatility with time-fixed effects and standard errors clustered by distinct default event (Table 15). The decreased statistical significance of CDS auction and other controls with standard errors clustered by distinct default event is likely due to my small dataset (as discussed in Section 7.1), and under my identification assumption clustering may not be necessary.[40]

8. Conclusion

In this paper, I investigate manufactured credit events and market participants' attempts to favorably move the prices of bonds included in CDS auction to gain more profitable positions around default and emerging from CDS auctions. There is no previous empirical research on evidence of these practices because of the limited data and small number of revealed cases. However, these cases are becoming more common, with three public cases in the past twelve months, and are not necessarily fair market activity. The CFTC has stated that these credit events may constitute market manipulation and casual empiricism suggests the ramifications of these events and bond price manipulation could undermine not only the CDS market but the entire credit derivatives market. In early 2019, the ISDA made a proposal to decrease these credit events, specifically "narrowly tailored credit events." While this proposal is an attempt to prevent additional events, the proposal

[40] See Bakirov and Székely (2005), Ibragimov and Müller (2010), Imbens and Kolesar (2016), Ibragimov and Müller (2016), Abadie et. Al (2017) for discussion of small sample problem and clustering methodology.

is very narrow and would only prevent a very certain type of credit event, not all forms of manipulation.[41]

To investigate manufactured credit events and this bond price manipulation before CDS auctions, I analyze bond return volatility around the time of default for bonds that are included in CDS auctions, either because they have CDS written on them or their reference entity does, compared to their counterparts not in CDS auctions. I use bond return volatility as a measure of indirect evidence of market participants manipulating bond prices before default and from default to auction as market participants try to favorably move prices to achieve more profitable CDS auction outcomes.

Using defaulted bonds over the 2005-2018 time period with pricing data in TRACE and sufficient data to measure bond illiquidity, firm fundamentals, and bond characteristics, I find a bond's inclusion in a CDS auction is significantly positively related to bond return volatility around the time of default. First, I run baseline regressions in which I control for bond illiquidity, credit risk, firm fundamentals, and other bond-level controls and find that a bond included in a CDS auction is associated with a higher bond return volatility around default, particularly in the six months prior to default. Several bond illiquidity measures are also significantly positively related to bond return volatility around the time of default.

As a robustness test, I use propensity score matching to create datasets of CDS auction bonds and control bonds that have a similar likelihood of being included in a CDS auction for each time period. The ATET and ATE of these propensity score matched

[41] Smith, Robert, 2019, "Isda's whack-a-mole fixes for credit default swaps merit scrutiny," *Financial Times*, Mar 7.

samples are positive and significant for all time periods and matching specifications. Further, CDS auction and bond illiquidity measures' significantly positive effect on bond return volatility around default in the baseline regressions remain robust to using propensity score matched samples. The significantly positive treatment effect of a bond's inclusion in CDS auction on bond return volatility for the time periods twelve and six months before default and when combined with the post default time period also persists when using double-robust estimators. Lastly, to control for the possible tendency of CDS auction bond defaults to occur during high market volatility times and for any market-wide variation in bond return volatility that is unexplained by my controls, I run my baseline regressions with time fixed-effects. I find that CDS auction and illiquidity measures are significantly positively related to bond return volatility with time fixed-effects and positively related to bond return volatility with time fixed effects and standard errors clustered by distinct default event.

Therefore, given that bonds included in CDS auctions are associated with higher bond return volatility around the time of default, I find indirect evidence of bond price manipulation around the time of default for bonds included in CDS auctions compared to their counterparts not in CDS auctions. This paper is thus the first to find empirical indication of market participants manipulating bond prices prior to CDS auctions as they strive for more profitable positions and auction outcomes and possibly of manufactured credit events that are not necessarily already publicized in the news. This paper is also the first to model factors influencing bond return volatility around the time of default and finds strong evidence that bond illiquidity is significantly positively related to bond return volatility around the time of default. To continue this analysis and investigation, the dataset could be expanded to include defaulted bonds not only included in TRACE or Compustat (by gathering data from other sources). This would further strengthen the results given the small size of my sample. As an extension of this paper, further research could examine the impact of a bond's inclusion in CDS auction on excess bond return volatility using a Merton model with stochastic interest rates and equity volatility as in Bao and Pan (2013).

9. Tables and Figures

Table 1: Time Period Names and Descriptions

Name	Description
12BDEFA	12 months before default to 29 days after default
12BDEF	12 months before default to default
6BDEFA	6 months before default to 29 days after default
6BDEF	6 months before default to default
DEFA	Default to 29 days after default

Table 2: Summary Statistics 12BDEFA

	Panel A			Panel B		Panel C	
	All Bonds			Bonds Not in CDS Auction		Bonds in CDS Auction	
VARIABLES	N	mean	std	mean	std	mean	std
Number of Trades	609	1,931	2,975	1,692	2,857	2,309	3,122
Volume Traded	609	622.2	911.9	507.5	731.2	803.5	111.9
Daily Return	599	-0.590	3.25	-0.252	1.15	-1.11	4.95
Annual Volatility	594	112.4	171.8	90.0	92.4	147.1	244.8
Rating	498	17.15	2.087	17.12	2.025	17.21	2.232
Age	602	5.847	4.701	4.965	3.722	7.285	5.684
Maturity	602	5.684	6.749	5.275	7.328	6.351	5.635
IRC	605	1.825	1.387	1.625	1.250	2.139	1.528
Bond Zero	609	54.32	30.72	54.51	32.77	54.02	27.25
Amihud	608	0.00697	0.0155	0.00572	0.00647	0.00894	0.0234
SD(IRC)	600	2.810	2.924	2.464	2.720	3.358	3.150
SD(Amihud)	603	0.0164	0.0332	0.0159	0.0390	0.0173	0.0211
B/A Spread	472	3.089	4.751	3.138	5.150	3.012	4.048
SD(B/A Spread)	456	0.998	1.816	0.932	1.834	1.102	1.787
Log(Amt)	602	19.81	0.927	19.72	0.824	19.96	1.058
CDS Auction	609	0.388	0.488	0	0	1	0
CDS Firm	609	0.798	0.401	0.684	0.464	0.979	0.144
EBIT/Assets	549	-0.0212	0.108	-0.0211	0.0806	-0.0215	0.141
Coverage Ratio	555	-0.262	8.178	-0.0603	7.840	-0.584	8.699
Sales/Assets	549	0.182	0.143	0.191	0.165	0.168	0.0963
RE/Assets	549	-0.531	0.747	-0.524	0.772	-0.542	0.707
NI/Assets	549	-0.0700	0.126	-0.0696	0.115	-0.0707	0.141

CF/Assets	549	-0.00591	0.0533	0.00400	0.0501	-0.0218	0.0545
Earnings/Assets	548	-0.0689	0.124	-0.0694	0.114	-0.0682	0.139
Leverage	549	0.422	0.846	0.408	0.796	0.446	0.922
Cash Flow Vol	545	0.0361	0.0266	0.0407	0.0267	0.0288	0.0248
log(Assets)	549	8.671	1.649	8.125	1.773	9.545	0.893
Earnings Vol	545	0.0447	0.0459	0.0492	0.0502	0.0376	0.0372
Sales Vol	545	0.0437	0.0519	0.0516	0.0608	0.0311	0.0289
Leverage Vol	545	0.159	0.249	0.151	0.230	0.171	0.276

Summary statistics for all bonds in my sample (Panel A), bonds not in CDS auction (Panel B), and bonds in CDS auction (Panel C) for time period 12BDEFA. Observations are reported at the bond level. *Number of* trades is the number of trades for a bond in the time period. *Volume Traded* is a bond's trading volume in $ million face value for the time period. *Daily Return* is the average of a bond's daily return over the time period reported in % and *Annual Volatility* is the annualized volatility of a bond's daily returns reported in %. *Rating* is a numerical translation of Moody's rating, where 1=Aaa and 21=C. *Age* is the time since issuance in years, and *Maturity* is a bond's time to maturity in years, measured at the day of default. *Bond Zero, Amihud, Amihud Vol, IRC, IRC Vol, B/A Spread,* and *SD(B/A Spread)* are defined and calculated as described in Section 5.4. *Bond Zero* is expressed in percent. *log(Amt)* is the natural log a bond's amount outstanding. *CDS Auction* indicates 1 if the bond is included in a CDS auction and 0 otherwise. *CDS Firm* indicates 1 if the bond's issuing firm has ever issued CDS (on any bond) and 0 otherwise. Using Compustat data, *EBIT/Assets* is defined as OIADP/AT, *Coverage Ratio* is defined as (OIADP + XINT)/XINT, *Sales/Assets* is defined as SALE/AT, *RE/Assets* is defined as RE/AT, *NI/Assets* is defined as NI/AT, *CF/Assets* is defined as OANCF/AT, *Earnings/Assets* is defined as IB/AT, *Leverage* is defined as (DLC + DLTT)/AT, and *log(Assets)* is defined as the natural log of total book assets, AT. *Cash Flow Vol, Earnings Vol, Sales Vol,* and *Leverage Vol* are calculated as described in Section 5.5 using the last five years of Compustat quarterly data.

Table 3: Correlation Matrix for 12BDEFA

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
(1) Rating	1.000																					
(2) Maturity	-0.090	1.000																				
(3) Age	0.140	0.216	1.000																			
(4) log(Amt)	-0.046	0.015	-0.334	1.000																		
(5) B/A Spread	-0.008	-0.033	-0.015	0.093	1.000																	
(6) SD(B/A Spread)	0.006	-0.056	0.036	0.133	0.857	1.000																
(7) Bond Zero	0.146	0.068	0.087	-0.446	-0.077	-0.108	1.000															
(8) Amihud	0.101	-0.013	0.463	-0.190	0.013	0.038	0.047	1.000														
(9) SD(Amihud)	0.058	-0.001	0.181	-0.123	-0.028	-0.028	0.022	0.749	1.000													
(10) IRC	-0.024	0.285	0.071	0.078	0.067	0.031	0.084	-0.028	0.036	1.000												
(11) SD(IRC)	-0.065	0.249	0.053	0.014	0.088	0.039	0.112	0.008	0.102	0.884	1.000											
(12) EBIT/Assets	0.151	0.002	0.072	-0.070	-0.249	-0.203	0.107	0.012	0.048	-0.015	-0.010	1.000										
(13) Coverage Ratio	0.144	-0.002	0.028	-0.100	-0.219	-0.189	0.157	-0.004	0.031	-0.014	-0.018	0.836	1.000									
(14) Sales/Assets	-0.019	-0.051	0.080	-0.323	-0.177	-0.171	0.136	0.075	0.053	0.028	-0.016	0.056	0.048	1.000								
(15) RE/Assets	-0.211	0.065	0.028	-0.053	-0.084	-0.032	-0.054	-0.052	0.015	-0.089	-0.097	0.134	0.150	-0.188	1.000							
(16) NI/Assets	0.069	0.024	0.129	-0.130	-0.177	-0.138	0.050	0.046	0.059	-0.101	-0.107	0.777	0.645	-0.032	0.346	1.000						
(17) log(Assets)	-0.030	0.342	0.300	0.412	-0.048	0.013	-0.184	0.134	0.022	0.185	0.120	0.046	0.001	-0.355	0.147	0.063	1.000					
(18) Cash Flow Vol	-0.222	-0.019	-0.080	-0.153	0.021	0.004	-0.013	0.029	0.019	-0.021	-0.058	-0.139	-0.104	0.259	0.028	-0.126	-0.352	1.000				
(19) Earnings Vol	-0.075	-0.075	-0.125	0.046	0.228	0.113	-0.040	-0.000	-0.036	-0.030	-0.023	-0.416	-0.348	0.128	-0.550	-0.487	-0.267	0.316	1.000			
(20) Leverage	0.021	-0.008	-0.045	0.037	0.132	0.135	0.017	0.003	-0.027	0.035	-0.007	-0.184	-0.169	0.115	-0.169	-0.206	-0.208	0.351	0.323	1.000		
(21) Sales Vol	-0.114	-0.022	0.001	-0.166	-0.084	-0.085	0.061	0.069	0.021	0.033	-0.004	-0.010	-0.028	0.435	-0.070	0.007	-0.241	0.588	0.212	0.063	1.000	
(22) Leverage Vol	0.022	-0.023	-0.089	0.059	0.262	0.177	0.008	-0.015	-0.039	0.028	0.005	-0.172	-0.137	0.110	-0.133	-0.177	-0.227	0.308	0.335	0.902	0.036	1.000

Correlations are shown among all variables included in baseline regressions for time period 12BDEFA. Other time periods exhibit similar correlations. Variables with a correlation greater than 0.75 are omitted from regressions except in specification 9.

Table 4: Baseline Regression across Time Periods

VARIABLES	12BDEFA	12BDEF	6BDEFA	6BDEF	DEFA
CDS Auction	**0.485****	**0.312***	**0.572***	**0.638****	**0.383***
	(2.451)	**(1.964)**	**(1.920)**	**(2.206)**	**(1.694)**
Rating	0.0315	0.0205	0.0620	0.0302	0.0759*
	(0.873)	(0.698)	(1.141)	(0.558)	(1.941)
Maturity	-0.0591***	-0.0330**	-0.0925***	-0.0732***	-0.0222
	(-3.211)	(-2.171)	(-3.379)	(-2.667)	(-1.169)
Age	0.0147	-0.00751	0.0834**	0.0592	-0.0449
	(0.593)	(-0.376)	(2.196)	(1.581)	(-1.499)
log(Amt)	0.331**	0.255**	0.381*	0.350*	-0.184
	(2.411)	(2.256)	(1.872)	(1.700)	(-1.250)
B/A Spread	0.0135	0.0219*	0.00885	0.0237	0.0409**
	(0.819)	(1.654)	(0.355)	(0.969)	(2.145)
Bond Zero	0.0169***	0.0161***	0.0153***	0.0228***	-0.00174
	(5.679)	(6.255)	(3.757)	(4.689)	(-0.554)
Amihud	48.01***	65.37***	-13.20	0.568	40.01***
	(3.684)	(6.514)	(-0.629)	(0.0286)	(4.861)
IRC	0.551***	0.385***	0.681***	0.472***	0.269***
	(7.765)	(6.088)	(9.554)	(5.839)	(9.344)
EBIT/Assets	0.722	-0.0725	3.907*	1.295	0.932
	(0.590)	(-0.0724)	(1.805)	(0.588)	(0.502)
Sales/Assets	-1.186*	-1.072**	-1.786*	-1.605	0.708
	(-1.792)	(-1.977)	(-1.790)	(-1.609)	(1.023)
RE/Assets	-0.292*	-0.289**	-0.302	-0.438*	0.120
	(-1.891)	(-2.294)	(-1.253)	(-1.824)	(0.681)
Leverage	-0.133	-0.0692	-0.299**	-0.226	0.110
	(-1.383)	(-0.878)	(-2.025)	(-1.532)	(1.010)
log(Assets)	-0.0958	-0.0362	-0.182	-0.124	0.148
	(-1.155)	(-0.523)	(-1.449)	(-0.974)	(1.605)
Cash Flow Vol	2.359	0.921	2.497	1.590	13.24***
	(0.614)	(0.295)	(0.422)	(0.271)	(3.028)
Earnings Vol	-1.163	-1.266	-1.016	-2.138	-0.748
	(-0.488)	(-0.653)	(-0.282)	(-0.599)	(-0.202)
Sales Vol	0.216	1.498	-0.108	1.389	-3.376
	(0.106)	(0.901)	(-0.0353)	(0.459)	(-1.575)
Constant	-7.260***	-6.051***	-7.863**	-7.506*	1.070
	(-2.763)	(-2.800)	(-2.020)	(-1.915)	(0.392)
Observations	335	334	331	330	247
Adjusted R-squared	0.318	0.321	0.314	0.197	0.447

*** p<0.01, ** p<0.05, * p<0.1

This table presents the baseline cross-sectional regression (specification 8) across all time periods. The dependent variable is σ_i, the annualized daily volatility for bond i. *CDS Auction* indicates 1 if the bond is included in a CDS auction and 0 otherwise. *Rating* is a numerical translation of Moody's rating, where 1=Aaa and 21=C. *Maturity* is a bond's time to maturity in years, and *Age* is the time since issuance in years, measured at the day of default. *log(Amt)* is the natural log a bond's amount outstanding. *B/A Spread, Bond Zero, Amihud,* and *IRC* are defined and calculated as described in Section 5.4. Using Compustat data, *EBIT/Assets* is defined as OIADP/AT, *Sales/Assets* is defined as SALE/AT, *RE/Assets* is defined as RE/AT, *Leverage* is defined as (DLC + DLTT)/AT, and *log(Assets)* is defined as the natural log of total book assets, AT. *Cash Flow Vol, Earnings Vol, and Sales Vol* are calculated as described in Section 5.5 using the last five years of Compustat quarterly data. *Note:* Coefficients are interpreted in the following way. CDS Auction's 0.485 coefficient for 12BDEFA means a bond included in a CDS auction is associated with a greater annual volatility of 48.5 percentage points. *t-statistics* are in parentheses.

Table 5: Various Baseline Regression Specifications for 12BDEFA

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6	(7) Model 7	(8) Model 8	(9) Model 9	(10) Model 10
CDS Auction	**0.572*****	**0.721*****	**0.414*****	**0.411****	**0.842*****	**0.831*****	**0.354***	**0.485****	**0.334***	**0.485**
	(4.014)	**(3.993)**	**(2.590)**	**(2.498)**	**(3.843)**	**(3.826)**	**(1.837)**	**(2.451)**	**(1.945)**	**(1.189)**
Rating		0.0531	0.116***	0.0497	0.0912**	0.0591	0.0878**	0.0315	0.0320	0.0315
		(1.537)	(3.435)	(1.612)	(2.002)	(1.464)	(2.234)	(0.873)	(0.979)	(0.984)
Maturity		-0.0251**	-0.0486***	-0.0602***	-0.0192	-0.0459**	-0.0331**	-0.0591***	-0.0302*	-0.0591
		(-2.001)	(-4.754)	(-4.814)	(-1.251)	(-2.276)	(-2.492)	(-3.211)	(-1.865)	(-1.250)
Age		0.0373*		0.00661	0.0402	0.0294		0.0147	-0.0144	0.0147
		(1.864)		(0.339)	(1.530)	(1.144)		(0.593)	(-0.634)	(0.694)
log(Amt)		0.283**		0.282***	0.0986	0.299*		0.331**	0.169	0.331
		(2.571)		(2.829)	(0.681)	(1.952)		(2.411)	(1.390)	(1.182)
B/A Spread		0.0363**		0.0194		0.0348*		0.0135	0.00757	0.0135
		(2.341)		(1.392)		(1.897)		(0.819)	(0.283)	(0.561)
SD(B/A Spread)									0.0332	
									(0.509)	
Bond Zero		0.0166***		0.0164***		0.0182***		0.0169***	0.0122***	0.0169
		(5.516)		(6.057)		(5.506)		(5.679)	(4.628)	(1.617)
Amihud			33.08***	49.62***			36.04***	48.01***	83.67***	48.01***
			(3.055)	(4.104)			(3.055)	(3.684)	(3.786)	(3.343)
SD(Amihud)									-4.797	
									(-1.490)	
IRC			0.688***	0.501***			0.749***	0.551***	0.405***	0.551***
			(12.05)	(8.320)			(11.68)	(7.765)	(3.379)	(3.583)
SD(IRC)									0.0622	
									(1.129)	
EBIT/Assets					0.526	-1.011	1.944*	0.722	2.549	0.722
					(0.405)	(-0.752)	(1.721)	(0.590)	(1.225)	(0.694)
Coverage Ratio									-0.0255	
									(-0.928)	
Sales/Assets					-0.697	-0.236	-1.176*	-1.186*	-0.941	-1.186
					(-0.923)	(-0.322)	(-1.825)	(-1.792)	(-1.608)	(-1.529)
RE/Assets					-0.422**	-0.378**	-0.244*	-0.292*	-0.0925	-0.292

					(-2.523)	(-2.184)	(-1.691)	(-1.891)	(-0.699)	(-1.164)
NI/Assets									-0.567	
									(-0.580)	
Leverage					-0.00420	-0.0667	-0.0701	-0.133	0.118	-0.133
					(-0.0359)	(-0.623)	(-0.697)	(-1.383)	(0.637)	(-0.995)
log(Assets)					-0.00736	0.0387	-0.0852	-0.0958	-0.0720	-0.0958
					(-0.0790)	(0.425)	(-1.297)	(-1.155)	(-0.981)	(-1.113)
Cash Flow Vol					-1.617	5.548	-3.479	2.359	1.713	2.359
					(-0.356)	(1.293)	(-0.883)	(0.614)	(0.515)	(0.997)
Earnings Vol					-2.632	-2.168	-0.765	-1.163	0.0379	-1.163
					(-0.938)	(-0.811)	(-0.315)	(-0.488)	(0.0184)	(-0.910)
Sales Vol					1.850	1.032	0.893	0.216	0.248	0.216
					(0.847)	(0.453)	(0.471)	(0.106)	(0.144)	(0.186)
Leverage Vol									-0.681	
									(-1.054)	
Constant	0.900***	-6.719***	-2.141***	-7.339***	-2.652	-7.722***	-0.847	-7.260***	-4.080*	-7.260
	(10.06)	(-2.929)	(-3.634)	(-3.538)	(-0.970)	(-2.650)	(-0.882)	(-2.763)	(-1.757)	(-1.226)
Cluster	No	No	No	No	No	No	No	No	No	Yes
Observations	594	377	481	377	433	335	432	335	321	335
Adjusted R-squared	0.025	0.136	0.300	0.315	0.083	0.141	0.313	0.318	0.346	0.318

*** p<0.01, ** p<0.05, * p<0.1

Reported are the baseline cross-sectional regressions for time period 12BDEFA. The dependent variable is σ_i, the annualized daily volatility for bond i. *CDS Auction* indicates 1 if the bond is included in a CDS auction and 0 otherwise. *Rating* is a numerical translation of Moody's rating, where 1=Aaa and 21=C. *Maturity* is a bond's time to maturity in years, and *Age* is the time since issuance in years, measured at the day of default. *log(Amt)* is the natural log a bond's amount outstanding. *B/A Spread*, *SD(B/A Spread)*, *Bond Zero*, *Amihud*, *SD(Amihud)*, *IRC*, and *SD(IRC)* are defined and calculated as described in Section 5.4. Using Compustat data, *EBIT/Assets* is defined as OIADP/AT, *Coverage Ratio* is defined as (OIADP + XINT)/XINT, *Sales/Assets* is defined as SALE/AT, *RE/Assets* is defined as RE/AT, *NI/Assets* is defined as NI/AT, *CF/Assets* is defined as OANCF/AT, *Earnings/Assets* is defined as IB/AT, *Leverage* is defined as (DLC + DLTT)/AT, and *log(Assets)* is defined as the natural log of total book assets, AT. *Cash Flow Vol*, *Earnings Vol*, *Sales Vol*, and *Leverage Vol* are calculated as described in Section 5.5 using the last five years of Compustat quarterly data. *Note:* Coefficients are interpreted in the following way. CDS Auction's 0.485 coefficient for 12BDEFA means a bond included in a CDS auction is associated with a greater annual volatility of 48.5 percentage points. *t-statistics* are in parentheses and cluster signifies clustered standard errors by distinct default event.

Table 6: Various Baseline Regression Specifications for 12BDEF

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
CDS Auction	**0.345*****	**0.359****	**0.470*****	**0.172**	**0.606*****	**0.485*****	**0.485****	**0.312***	**0.264***	**0.312**
	(2.629)	**(2.426)**	**(2.941)**	**(1.296)**	**(3.003)**	**(2.717)**	**(2.484)**	**(1.964)**	**(1.733)**	**(1.069)**
Rating		0.0445	0.112***	0.0368	0.0765*	0.0464	0.0777*	0.0205	0.0274	0.0205
		(1.576)	(3.262)	(1.475)	(1.823)	(1.396)	(1.924)	(0.698)	(0.940)	(0.786)
Maturity		-0.0151	-0.0171*	-0.0198**	-0.0121	-0.0261	-0.0198	-0.0330**	-0.00680	-0.0330
		(-1.473)	(-1.688)	(-2.099)	(-0.858)	(-1.563)	(-1.437)	(-2.171)	(-0.465)	(-1.088)
Age		0.0320*		-0.00921	0.0398	0.0280		-0.00751	-0.0422**	-0.00751
		(1.946)		(-0.587)	(1.645)	(1.323)		(-0.376)	(-2.097)	(-0.410)
log(Amt)		0.251***		0.260***	0.118	0.230*		0.255**	0.172	0.255
		(2.781)		(3.203)	(0.882)	(1.800)		(2.256)	(1.597)	(1.290)
B/A Spread		0.0423***		0.0285**		0.0402***		0.0219*	0.00862	0.0219
		(3.393)		(2.562)		(2.702)		(1.654)	(0.362)	(1.151)
SD(B/A Spread)									0.0361	
									(0.622)	
Bond Zero		0.0137***		0.0152***		0.0154***		0.0161***	0.0139***	0.0161*
		(5.224)		(6.502)		(5.291)		(6.255)	(5.521)	(1.775)
Amihud			30.49***	63.15***			34.82***	65.37***	124.3***	65.37**
			(2.892)	(6.793)			(3.010)	(6.514)	(6.746)	(2.110)
SD(Amihud)									-10.20***	
									(-3.611)	
IRC			0.347***	0.364***			0.344***	0.385***	0.141	0.385***
			(5.222)	(6.858)			(4.612)	(6.088)	(1.283)	(4.780)
SD(IRC)									0.119**	
									(2.264)	
EBIT/Assets					0.201	-1.216	1.042	-0.0725	1.796	-0.0725
					(0.168)	(-1.099)	(0.892)	(-0.0724)	(0.959)	(-0.0995)
Coverage Ratio									-0.0210	
									(-0.853)	
Sales/Assets					-0.794	-0.225	-1.181*	-1.072**	-1.061**	-1.072*
					(-1.144)	(-0.371)	(-1.778)	(-1.977)	(-1.986)	(-1.671)
RE/Assets					-0.418***	-0.332**	-0.376**	-0.289**	-0.124	-0.289
					(-2.715)	(-2.320)	(-2.533)	(-2.294)	(-1.050)	(-1.399)

NI/Assets									-0.733	
									(-0.837)	
Leverage					0.00545	-0.0383	-0.0221	-0.0692	0.106	-0.0692
					(0.0506)	(-0.434)	(-0.212)	(-0.878)	(0.637)	(-0.841)
log(Assets)					-0.0136	0.0368	-0.0253	-0.0362	-0.0264	-0.0362
					(-0.159)	(0.481)	(-0.372)	(-0.523)	(-0.398)	(-0.814)
Cash Flow Vol					-2.865	3.709	-4.360	0.921	0.0441	0.921
					(-0.686)	(1.050)	(-1.073)	(0.295)	(0.0147)	(0.464)
Earnings Vol					-2.521	-2.008	-1.701	-1.266	-0.104	-1.266
					(-0.976)	(-0.914)	(-0.679)	(-0.653)	(-0.0567)	(-1.013)
Sales Vol					2.517	1.590	2.268	1.498	2.160	1.498
					(1.252)	(0.848)	(1.162)	(0.901)	(1.209)	(1.423)
Leverage Vol									-0.492	
									(-0.849)	
Constant	0.861***	-5.926***	-1.709***	-6.704***	-2.782	-6.137**	-0.722	-6.051***	-4.521**	-6.051
	(10.50)	(-3.132)	(-2.821)	(-3.955)	(-1.106)	(-2.527)	(-0.731)	(-2.800)	(-2.184)	(-1.339)
Cluster	No	No	No	No	No	No	No	No	No	Yes
Observations	590	375	481	375	433	334	432	334	320	334
Adjusted R-squared	0.010	0.115	0.118	0.310	0.068	0.125	0.126	0.321	0.350	0.321

*** p<0.01, ** p<0.05, * p<0.1

Reported are the baseline cross-sectional regressions for time period 12BDEF. All variables are defined as in Table 5. *Note:* Coefficients are interpreted in the following way. CDS Auction’s 0.485 coefficient for 12BDEFA means a bond included in a CDS auction is associated with a greater annual volatility of 48.5 percentage points. *t-statistics* are in parentheses and cluster signifies clustered standard errors by distinct default event.

Table 7: Various Baseline Regression Specifications for 6BDEFA

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
CDS Auction	**0.923*** **	**1.112*** **	**0.637*** **	**0.630** **	**1.357*** **	**1.268*** **	**0.389**	**0.572* **	**0.375**	**0.572**
	(4.402)	**(4.107)**	**(2.746)**	**(2.547)**	**(4.171)**	**(3.876)**	**(1.395)**	**(1.920)**	**(1.446)**	**(1.176)**
Rating		0.0944*	0.181***	0.104**	0.154**	0.106*	0.143**	0.0620	0.0661	0.0620
		(1.826)	(3.711)	(2.250)	(2.278)	(1.726)	(2.543)	(1.141)	(1.330)	(1.141)
Maturity		-0.0351*	-0.0744***	-0.113***	-0.0328	-0.0746**	-0.0421**	-0.0925***	-0.0600**	-0.0925
		(-1.877)	(-5.087)	(-5.958)	(-1.444)	(-2.458)	(-2.234)	(-3.379)	(-2.510)	(-1.209)
Age		0.0415		0.0602**	0.0527	0.0308		0.0834**	0.0569*	0.0834
		(1.385)		(1.981)	(1.352)	(0.794)		(2.196)	(1.691)	(1.280)
log(Amt)		0.386**		0.308**	0.179	0.395*		0.381*	0.179	0.381
		(2.333)		(2.062)	(0.829)	(1.721)		(1.872)	(0.985)	(1.159)
B/A Spread		0.0429*		0.0134		0.0356		0.00885	0.0197	0.00885
		(1.937)		(0.669)		(1.268)		(0.355)	(0.491)	(0.233)
SD(B/A Spread)									0.0254	
									(0.269)	
Bond Zero		0.0195***		0.0162***		0.0203***		0.0153***	0.00970***	0.0153
		(4.695)		(4.305)		(4.459)		(3.757)	(2.663)	(1.478)
Amihud			12.47	-14.47			23.02	-13.20	-5.076	-13.20
			(0.794)	(-0.742)			(1.346)	(-0.629)	(-0.136)	(-0.350)
SD(Amihud)									2.319	
									(0.234)	
IRC			0.688***	0.555***			0.803***	0.681***	0.729***	0.681**
			(13.43)	(9.676)			(13.59)	(9.554)	(5.494)	(2.486)
SD(IRC)									-0.0632	
									(-0.884)	
EBIT/Assets					0.498	-1.961	3.906**	3.907*	10.66**	3.907
					(0.241)	(-0.834)	(2.230)	(1.805)	(2.262)	(1.272)
Coverage Ratio									-0.0943*	
									(-1.678)	
Sales/Assets					-0.960	-0.568	-1.441	-1.786*	-1.257	-1.786
					(-0.856)	(-0.507)	(-1.565)	(-1.790)	(-1.404)	(-1.409)
RE/Assets					-0.540**	-0.586**	-0.130	-0.302	-0.00136	-0.302
					(-2.178)	(-2.158)	(-0.628)	(-1.253)	(-0.00633)	(-1.009)
NI/Assets									-0.0243	

									(-0.0163)	
Leverage					-0.0394	-0.0959	-0.162	-0.299**	-0.0307	-0.299
					(-0.226)	(-0.580)	(-1.123)	(-2.025)	(-0.108)	(-1.228)
log(Assets)					-0.00913	0.0449	-0.0914	-0.182	-0.180	-0.182
					(-0.0661)	(0.322)	(-0.966)	(-1.449)	(-1.599)	(-1.212)
Cash Flow Vol					-2.306	7.800	-4.940	2.497	1.493	2.497
					(-0.343)	(1.175)	(-0.880)	(0.422)	(0.288)	(0.829)
Earnings Vol					-2.749	-3.642	0.00747	-1.016	1.154	-1.016
					(-0.662)	(-0.894)	(0.00216)	(-0.282)	(0.361)	(-0.594)
Sales Vol					2.226	0.951	1.289	-0.108	-0.432	-0.108
					(0.689)	(0.275)	(0.478)	(-0.0353)	(-0.166)	(-0.0628)
Leverage Vol									-0.892	
									(-0.920)	
Constant	1.029***	-9.500***	-3.088***	-8.556***	-5.142	-10.43**	-1.622	-7.863**	-3.657	-7.863
	(7.764)	(-2.754)	(-3.645)	(-2.747)	(-1.258)	(-2.382)	(-1.180)	(-2.020)	(-1.056)	(-1.201)
Cluster	No	No	No	No	No	No	No	No	No	Yes
Observations	576	372	472	372	426	331	425	331	317	331
Adjusted R-squared	0.031	0.119	0.339	0.296	0.088	0.119	0.368	0.314	0.292	0.314

*** p<0.01, ** p<0.05, * p<0.1

Reported are the baseline cross-sectional regressions for time period 6BDEFA. All variables are defined as in Table 5. *Note:* Coefficients are interpreted in the following way. CDS Auction's 0.485 coefficient for 12BDEFA means a bond included in a CDS auction is associated with a greater annual volatility of 48.5 percentage points. *t-statistics* are in parentheses and cluster signifies clustered standard errors by distinct default event.

Table 8: Various Baseline Regression Specifications for 6BDEF

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6	(7) Model 7	(8) Model 8	(9) Model 9	(10) Model 10
CDS Auction	**0.525*** **	**0.653*** **	**0.778*** **	**0.413***	**0.885*** **	**0.892*** **	**0.772*** **	**0.638** **	**0.701** **	**0.638**
	(2.872)	**(2.636)**	**(3.364)**	**(1.732)**	**(3.089)**	**(2.971)**	**(2.711)**	**(2.206)**	**(2.405)**	**(1.163)**
Rating		0.0614	0.156***	0.0706	0.106*	0.0627	0.125**	0.0302	0.0654	0.0302
		(1.291)	(3.164)	(1.559)	(1.782)	(1.110)	(2.140)	(0.558)	(1.165)	(0.748)
Maturity		-0.0291*	-0.0179	-0.0450***	-0.0197	-0.0585**	-0.0238	-0.0732***	-0.0601**	-0.0732
		(-1.693)	(-1.242)	(-2.652)	(-0.986)	(-2.084)	(-1.207)	(-2.667)	(-2.194)	(-1.088)
Age		0.0423		0.0405	0.0565*	0.0369		0.0592	0.0417	0.0592
		(1.536)		(1.386)	(1.650)	(1.037)		(1.581)	(1.096)	(1.240)
log(Amt)		0.403***		0.311**	0.148	0.373*		0.350*	0.254	0.350
		(2.652)		(2.127)	(0.755)	(1.723)		(1.700)	(1.216)	(1.252)
B/A Spread		0.0559***		0.0321*		0.0451*		0.0237	0.0207	0.0237
		(2.811)		(1.664)		(1.781)		(0.969)	(0.458)	(0.707)
SD(B/A Spread)									0.0583	
									(0.547)	
Bond Zero		0.0226***		0.0218***		0.0254***		0.0228***	0.0213***	0.0228*
		(5.024)		(5.027)		(5.029)		(4.689)	(4.126)	(1.682)
Amihud			6.743	4.125			9.817	0.568	12.97	0.568
			(0.455)	(0.228)			(0.594)	(0.0286)	(0.317)	(0.0219)
SD(Amihud)									-5.825	
									(-0.479)	
IRC			0.267***	0.408***			0.247***	0.472***	0.227	0.472**
			(4.280)	(6.297)			(3.451)	(5.839)	(1.414)	(2.458)
SD(IRC)									0.121	
									(1.420)	
EBIT/Assets					-0.264	-3.149	0.893	1.295	6.802	1.295
					(-0.145)	(-1.452)	(0.486)	(0.588)	(1.232)	(0.624)
Coverage Ratio									-0.0742	
									(-1.142)	
Sales/Assets					-0.986	-0.605	-1.129	-1.605	-1.198	-1.605
					(-0.997)	(-0.586)	(-1.169)	(-1.609)	(-1.141)	(-1.428)
RE/Assets					-0.490**	-0.600**	-0.413*	-0.438*	-0.208	-0.438
					(-2.240)	(-2.397)	(-1.910)	(-1.824)	(-0.848)	(-1.356)
NI/Assets									-0.760	

									(-0.446)	
Leverage					0.0168	-0.0644	-0.0248	-0.226	0.116	-0.226
					(0.110)	(-0.423)	(-0.164)	(-1.532)	(0.359)	(-1.088)
log(Assets)					-0.00492	0.0358	0.0257	-0.124	-0.0913	-0.124
					(-0.0402)	(0.275)	(0.260)	(-0.974)	(-0.700)	(-1.054)
Cash Flow Vol					-3.327	6.027	-4.518	1.590	2.749	1.590
					(-0.564)	(0.989)	(-0.769)	(0.271)	(0.462)	(0.583)
Earnings Vol					-2.575	-3.832	-1.961	-2.138	-0.121	-2.138
					(-0.705)	(-1.026)	(-0.542)	(-0.599)	(-0.0334)	(-1.156)
Sales Vol					2.862	1.865	2.796	1.389	2.239	1.389
					(1.007)	(0.588)	(0.994)	(0.459)	(0.654)	(0.923)
Leverage Vol									-1.275	
									(-1.148)	
Constant	1.008***	-9.571***	-2.150**	-8.479***	-3.871	-9.629**	-1.613	-7.506*	-6.323	-7.506
	(8.791)	(-3.024)	(-2.472)	(-2.787)	(-1.053)	(-2.354)	(-1.127)	(-1.915)	(-1.587)	(-1.306)
Cluster	No	No	No	No	No	No	No	No	No	Yes
Observations	577	370	469	370	423	330	422	330	316	330
Adjusted R-squared	0.012	0.107	0.084	0.192	0.059	0.115	0.081	0.197	0.156	0.197

*** p<0.01, ** p<0.05, * p<0.1

Reported are the baseline cross-sectional regressions for time period 6BDEF. All variables are defined as in Table 5. *Note:* Coefficients are interpreted in the following way. CDS Auction's 0.485 coefficient for 12BDEFA means a bond included in a CDS auction is associated with a greater annual volatility of 48.5 percentage points. *t-statistics* are shown in parentheses and cluster signifies clustered standard errors by distinct default event.

Table 9: Various Baseline Regression Specifications for DEFA

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
CDS Auction	**0.993*** **	**1.106*** **	**0.755*** **	**0.695*** **	**1.132*** **	**0.731*** **	**0.553***	**0.383***	**0.527** **	**0.383**
	(4.570)	**(4.215)**	**(2.913)**	**(2.943)**	**(3.477)**	**(2.755)**	**(1.815)**	**(1.694)**	**(2.073)**	**(1.275)**
Rating		0.0195	0.0563	0.0461	0.0889	0.0621	0.0784	0.0759*	0.0687	0.0759
		(0.410)	(1.035)	(1.103)	(1.320)	(1.314)	(1.290)	(1.941)	(1.523)	(1.061)
Maturity		-0.00389	-0.0266	-0.0308	-0.0223	0.000131	-0.0277	-0.0222	-0.0285	-0.0222
		(-0.163)	(-1.467)	(-1.444)	(-1.002)	(0.00580)	(-1.364)	(-1.169)	(-1.407)	(-1.549)
Age		0.0245		-0.00486	0.0409	-0.00505		-0.0449	-0.0498	-0.0449*
		(0.774)		(-0.170)	(1.067)	(-0.144)		(-1.499)	(-1.542)	(-1.787)
log(Amt)		-0.273*		-0.219	0.192	-0.151		-0.184	-0.165	-0.184
		(-1.784)		(-1.649)	(0.889)	(-0.839)		(-1.250)	(-1.011)	(-1.127)
B/A Spread		0.0224		0.0269		0.0429*		0.0409**	0.0414	0.0409*
		(0.897)		(1.240)		(1.849)		(2.145)	(1.020)	(1.773)
SD(B/A Spread)									0.0167	
									(0.189)	
Bond Zero		-0.00205		-0.00179		-0.00180		-0.00174	-0.00116	-0.00174
		(-0.492)		(-0.492)		(-0.472)		(-0.554)	(-0.341)	(-0.453)
Amihud			45.08***	38.78***			47.99***	40.01***	8.775	40.01***
			(3.950)	(3.891)			(3.962)	(4.861)	(0.328)	(6.663)
SD(Amihud)									33.85**	
									(2.426)	
IRC			0.280***	0.279***			0.287***	0.269***	0.109	0.269***
			(8.427)	(8.708)			(8.200)	(9.344)	(1.054)	(4.206)
SD(IRC)									0.101	
									(1.521)	
EBIT/Assets					0.335	2.704	0.709	0.932	5.125	0.932
					(0.166)	(1.200)	(0.386)	(0.502)	(1.148)	(0.517)
Coverage Ratio									-0.0492	
									(-1.040)	
Sales/Assets					0.672	1.543*	0.106	0.708	0.992	0.708
					(0.599)	(1.841)	(0.106)	(1.023)	(1.272)	(0.977)
RE/Assets					-0.0673	0.190	0.0332	0.120	0.135	0.120
					(-0.262)	(0.886)	(0.143)	(0.681)	(0.685)	(1.122)
NI/Assets									-0.157	

									(-0.114)	
Leverage					0.0839	0.101	0.104	0.110	0.325	0.110
					(0.481)	(0.766)	(0.661)	(1.010)	(1.154)	(0.831)
log(Assets)					-0.0172	0.132	0.0390	0.148	0.164	0.148
					(-0.122)	(1.180)	(0.371)	(1.605)	(1.572)	(1.646)
Cash Flow Vol					7.471	15.53***	7.770	13.24***	19.00***	13.24**
					(1.100)	(2.919)	(1.256)	(3.028)	(4.006)	(2.310)
Earnings Vol					-1.887	-0.402	-0.644	-0.748	-1.054	-0.748
					(-0.460)	(-0.0889)	(-0.173)	(-0.202)	(-0.250)	(-0.248)
Sales Vol					-1.869	-4.095	-2.063	-3.376	-4.611**	-3.376
					(-0.592)	(-1.581)	(-0.711)	(-1.575)	(-2.005)	(-1.431)
Leverage Vol									-1.206	
									(-1.215)	
Constant	0.893***	5.856*	-0.776	3.806	-4.699	1.073	-1.707	1.070	0.581	1.070
	(6.383)	(1.865)	(-0.819)	(1.392)	(-1.144)	(0.322)	(-1.132)	(0.392)	(0.195)	(0.325)
Cluster	No	No	No	No	No	No	No	No	No	Yes
Observations	524	279	423	278	385	248	381	247	222	247
Adjusted R-squared	0.037	0.083	0.210	0.312	0.034	0.117	0.204	0.406	0.435	0.406

*** p<0.01, ** p<0.05, * p<0.1

Reported are the baseline cross-sectional regressions for time period DEFA. All variables are defined as in Table 5. *Note:* Coefficients are interpreted in the following way. CDS Auction's 0.485 coefficient for 12BDEFA means a bond included in a CDS auction is associated with a greater annual volatility of 48.5 percentage points. *t-statistics* are shown in parentheses and cluster signifies clustered standard errors by distinct default event.

Table 10: Propensity Score Matching Probit Model for 12BDEFA

CDS Auction	12BDEFA	12BDEF	6BDEFA	6BDEF	DEFA
Rating	-0.032	-0.033	-0.032	-0.035	-0.060
	(-0.88)	(-0.89)	(-0.87)	(-0.94)	(-1.55)
EBIT/Assets	3.984**	4.103**	3.985**	4.084**	4.675**
	(2.14)	(2.17)	(2.14)	(2.17)	(2.37)
Sales/Assets	2.064***	2.055***	2.069***	2.052***	2.114***
	(3.09)	(3.06)	(3.09)	(3.04)	(3.09)
RE/Assets	0.006	0.016	0.011	0.031	0.001
	(0.05)	(0.11)	(0.07)	(0.22)	(0.01)
Leverage	0.185*	0.185*	0.186*	0.188*	0.197*
	(1.70)	(1.70)	(1.70)	(1.73)	(1.74)
log(Assets)	0.447***	0.436***	0.443***	0.429***	0.450***
	(8.24)	(7.98)	(8.13)	(7.80)	(7.65)
Cash Flow Vol	-4.086	-4.258	-4.170	-4.389	-4.488
	(-0.89)	(-0.93)	(-0.91)	(-0.96)	(-0.94)
Earnings Vol	-1.429	-1.461	-1.379	-1.285	-1.666
	(-0.52)	(-0.53)	(-0.51)	(-0.47)	(-0.60)
Sales Vol	-5.820**	-6.169**	-5.835**	-6.084**	-5.741**
	(-2.03)	(-2.11)	(-2.03)	(-2.08)	(-1.96)
Observations	436	434	429	424	338
Pseudo R2	0.228	0.225	0.225	0.219	0.224

*** p<0.01, ** p<0.05, * p<0.1

This table presents the estimates of the probability of a bond's inclusion in CDS auction, obtained using a probit model. Propensity scores are estimated based on the model parameters. Variables are defined as in Table 4. *z-statistics* are shown in parentheses.

Table 11: Treatment Effects using Propensity Score Matching (Teffects)

	(1) 12BDEFA NN(1)	(2) 12BDEFA NN(3)	(7) 12BDEF NN(1)	(8) 12BDEF NN(3)	(3) 6BDEFA NN(1)	(4) 6BDEFA NN(3)	(1) 6BDEF NN(1)	(2) 6BDEF NN(3)	(5) DEFA NN(1)	(6) DEFA NN(3)
ATET	1.171***	0.996***	0.798***	0.754**	1.533***	1.575***	1.210***	1.088***	1.366***	1.374***
Robust S.E	0.346	0.300	0.247	0.295	0.430	0.401	0.283	0.301	0.374	0.370
	(3.38)	(3.31)	(3.23)	(2.55)	(3.61)	(3.92)	(4.27)	(3.61)	(3.65)	(3.71)
ATE	1.056***	1.097***	0.535***	0.637***	1.766***	1.911***	0.899***	1.020***	0.774***	0.799***
Robust S.E	0.242	0.246	0.178	0.200	0.341	0.352	0.274	0.297	0.235	0.228
	(4.37)	(4.47)	(3.00)	(3.18)	(5.18)	(5.43)	(3.28)	(3.43)	(3.29)	(3.50)

*** p<0.01, ** p<0.05, * p<0.1

Treatment effects are shown across all time periods using propensity score matching. As defined in Section 7.2, the ATET is the average treatment effect on the treated, and the ATE is the average treatment effect, in which the treatment is a bond's inclusion in CDS auction and the effect is on the dependent variable, σ_i, the annualized daily volatility for bond i. NN(1) is nearest neighbor matching method and NN(3) is three nearest neighbors matching method. *Note:* Treatment effects are interpreted in the following way. The ATET of 1.171 for 12BDEFA NN(1) estimates that the average bond return volatility for a CDS auction bond is 117.1 percentage points higher than if it is not in a CDS auction. The ATE of 1.056 for 12BDEFA NN(1) estimates that the bond return volatility is 105.6 percentage points higher when a bond is included in a CDS auction. Robust standard errors are included and *z-statistics* are shown in parentheses.

Table 12: Regressions Using Propensity Score Matched Sample (Teffects)

	(1) 12BDEFA NN(1)	(2) 12BDEFA NN(3)	(3) 12BDEF NN(1)	(4) 12BDEF NN(3)	(5) 6BDEFA NN(1)	(6) 6BDEFA NN(3)	(7) 6BDEF NN(1)	(8) 6BDEF NN(3)	(9) DEFA NN(1)	(10) DEFA NN(3)
CDS Auction	**0.471****	**0.594****	**0.359****	**0.461****	**0.790****	**0.473**	**1.140*****	**0.879****	**0.262**	**0.375**
	(1.988)	**(2.298)**	**(1.973)**	**(2.401)**	**(2.227)**	**(1.197)**	**(3.036)**	**(2.360)**	**(0.861)**	**(1.384)**
Rating	-0.0280	-0.00489	-0.000918	-0.0201	0.126	0.133	0.0937	0.0870	0.298***	0.207***
	(-0.475)	(-0.0748)	(-0.0200)	(-0.400)	(1.398)	(1.330)	(0.884)	(0.901)	(3.902)	(3.271)
Maturity	-0.0579***	-0.0642***	-0.0106	-0.0346**	-0.120***	-0.0991***	-0.0857**	-0.0711**	-0.0143	-0.0100
	(-2.638)	(-3.023)	(-0.590)	(-2.243)	(-3.516)	(-3.044)	(-2.398)	(-2.409)	(-0.619)	(-0.533)
Age	0.0499*	0.0125	-0.00466	-0.00880	0.142***	0.0903*	0.125**	0.0905*	-0.0939**	-0.0362
	(1.660)	(0.398)	(-0.189)	(-0.337)	(3.152)	(1.922)	(2.518)	(1.880)	(-2.173)	(-0.974)
log(Amt)	0.616***	0.535***	0.513***	0.491***	0.712***	0.546**	0.810***	0.730***	-0.620***	-0.322*
	(3.568)	(3.161)	(3.370)	(3.468)	(2.692)	(2.134)	(2.882)	(2.631)	(-2.831)	(-1.879)
B/A Spread	-0.0212	-0.0300	-0.0186	-0.0195	0.0334	0.0305	-0.0277	0.00274	-0.0368	-0.0300
	(-0.775)	(-0.851)	(-0.716)	(-0.743)	(0.692)	(0.588)	(-0.380)	(0.0463)	(-0.648)	(-0.707)
Bond Zero	0.0337***	0.0330***	0.0325***	0.0358***	0.0317***	0.0252***	0.0441***	0.0476***	-0.0171***	-0.0135**
	(6.780)	(6.991)	(7.359)	(8.002)	(4.884)	(3.876)	(5.716)	(5.495)	(-2.882)	(-2.414)
Amihud	75.74***	94.12***	127.6***	122.7***	-43.92*	-38.68	-28.40	-21.55	23.23***	29.94***
	(3.227)	(3.624)	(6.885)	(6.311)	(-1.761)	(-1.347)	(-0.989)	(-0.794)	(3.601)	(4.229)
IRC	0.490***	0.464***	0.389***	0.332***	0.723***	0.704***	0.422***	0.525***	0.304***	0.289***
	(4.928)	(4.386)	(4.372)	(3.479)	(7.077)	(5.996)	(2.944)	(3.897)	(7.914)	(7.404)
EBIT/Assets	22.10***	21.32***	11.31**	15.39***	17.08*	21.75**	9.094	5.690	-2.865	-1.952
	(4.002)	(3.709)	(2.506)	(3.274)	(1.893)	(2.337)	(0.947)	(0.751)	(-0.602)	(-0.494)
Sales/Assets	-2.622**	-2.924**	-1.424	-1.982**	-2.141	-1.228	0.480	-0.652	1.369	-0.211
	(-2.418)	(-2.374)	(-1.438)	(-1.990)	(-1.071)	(-0.674)	(0.262)	(-0.360)	(1.142)	(-0.211)
RE/Assets	-1.506***	-1.009***	-0.844***	-1.008***	-0.682	-0.865	-1.215*	-0.541	0.680	0.645
	(-3.775)	(-2.719)	(-3.141)	(-3.899)	(-1.269)	(-1.371)	(-1.948)	(-1.100)	(1.515)	(1.394)

Leverage	-0.213	-0.249	-0.108	-0.117	-0.574*	-0.402	-0.287	-0.497	0.377	0.229
	(-1.082)	(-1.237)	(-0.690)	(-0.752)	(-1.813)	(-1.334)	(-0.879)	(-1.559)	(1.551)	(1.117)
log(Assets)	-0.633***	-0.363***	-0.452***	-0.396***	-0.346*	-0.266	-0.453**	-0.354*	0.391**	0.206
	(-4.781)	(-2.788)	(-4.330)	(-3.725)	(-1.803)	(-1.335)	(-2.356)	(-1.756)	(2.428)	(1.487)
Cash Flow Vol	-5.782	-4.229	-4.316	-6.793	3.765	-5.314	-3.156	2.745	12.85	16.44**
	(-0.730)	(-0.497)	(-0.636)	(-0.970)	(0.284)	(-0.403)	(-0.233)	(0.197)	(1.423)	(2.009)
Earnings Vol	7.678	9.739	6.810	5.057	10.18	5.236	0.482	4.584	3.046	4.293
	(1.188)	(1.364)	(1.368)	(0.910)	(1.023)	(0.474)	(0.0402)	(0.419)	(0.424)	(0.612)
Sales Vol	4.211	5.442	0.201	4.622	-3.681	3.183	-0.480	-4.022	-2.213	-1.501
	(0.717)	(0.829)	(0.0516)	(0.992)	(-0.359)	(0.306)	(-0.0487)	(-0.461)	(-0.329)	(-0.250)
Constant	-8.108**	-9.163***	-8.464***	-8.102***	-15.41***	-12.13**	-16.66***	-15.65***	4.620	1.451
	(-2.335)	(-2.607)	(-2.760)	(-2.836)	(-2.775)	(-2.233)	(-2.869)	(-2.899)	(1.122)	(0.413)
Observations	229	210	218	210	234	213	213	210	148	164
Adjusted R-squared	0.470	0.477	0.475	0.526	0.432	0.398	0.312	0.265	0.517	0.488

*** p<0.01, ** p<0.05, * p<0.1

This table shows the results of propensity score estimation using baseline regression specification 8 and NN(1) and NN(3) matched samples across all time periods. NN(1) and NN(3) are defined as in Table 11 and all variables are defined as in Table 4. *Note:* Coefficients are interpreted in the following way. CDS Auction's 0.471 coefficient for 12BDEFA means a bond included in a CDS auction is associated with a greater annual volatility of 48.5 percentage points. *t-statistics* are in parentheses.

Table 13: Treatment Effects using Double Robustness (Teffects AIPW and IPWRA)

VARIABLES	12BDEFA AIPW	12BDEFA IPWRA	12BDEF AIPW	12BDEF IPWRA	6BDEFA AIPW	6BDEFA IPWRA	6BDEF AIPW	6BDEF IPWRA	DEFA AIPW	DEFA IPWRA
POmeans										
Non-CDS Auction	0.800***	0.839***	0.734***	0.777**	0.944***	1.003***	0.842***	0.905***	0.942***	0.868***
Robust S.E	0.057	0.046	0.055	0.041	0.080	0.058	0.083	0.049	0.145	0.069
	(13.93)	(18.32)	(13.22)	(18.81)	(11.76)	(17.21)	(10.15)	(18.24)	(6.49)	(12.45)
CDS Auction	1.417***	1.344***	1.265***	1.234**	1.433***	1.160***	1.599***	1.406***	1.088***	1.185***
Robust S.E	0.311	0.294	0.261	0.237	0.366	0.327	0.387	0.342	0.268	0.238
	(4.56)	(4.57)	(4.85)	(5.21)	(3.91)	(3.55)	(4.13)	(4.11)	(4.07)	(4.98)
ATET		0.552**		0.378**		0.783**		0.702**		0.403*
Robust S.E		0.242		0.190		0.358		0.346		0.238
		(2.28)		(1.99)		(2.18)		(2.03)		(1.69)
ATE	0.617**	0.505*	0.531**	0.459**	0.489***	0.157	0.757*	0.500	0.146	0.317
Robust S.E	0.310	0.292	0.265	0.232	0.383	0.328	0.402	0.341	0.301	0.235
	(1.95)	(1.73)	(2.01)	(1.97)	(1.28)	(0.48)	(1.88)	(1.47)	(0.48)	(1.35)

*** p<0.01, ** p<0.05, * p<0.1

Treatment effects are shown across all time periods using AIPW and IPWRA double robust estimators, explained in Section 7.3. As defined in Section 7.3, POmeans is the potential-outcome means, the ATET is the average treatment effect on the treated, and the ATE is the average treatment effect, in which the treatment is a bond's inclusion in CDS auction and the effect is on the dependent variable, σ_i, the annualized daily volatility for bond i. The ATET cannot be measured using the AIPW double-robust estimators. *Note:* treatment effects are interpreted in the following way. The POmeans of 0.839 and 1.355 for 12BDEFA IPWRA measures the average potential outcome, or price volatility, as 83.8% for bonds not in CDS auction and 134.4% for bond in CDS auction. The ATET of 0.552 for 12BDEFA IPWRA estimates that the average bond return volatility for a CDS auction bond is 55.2 percentage points higher than if it is not in a CDS auction. The ATE of 0.505 for 12BDEFA IPWRA estimates that the bond return volatility is 50.5 percentage points higher when a bond is included in a CDS auction. Robust standard errors are included and *z-statistics* are shown in parentheses.

Figure 1: Time Distribution of CDS Auction vs. Non-CDS Auction Defaults

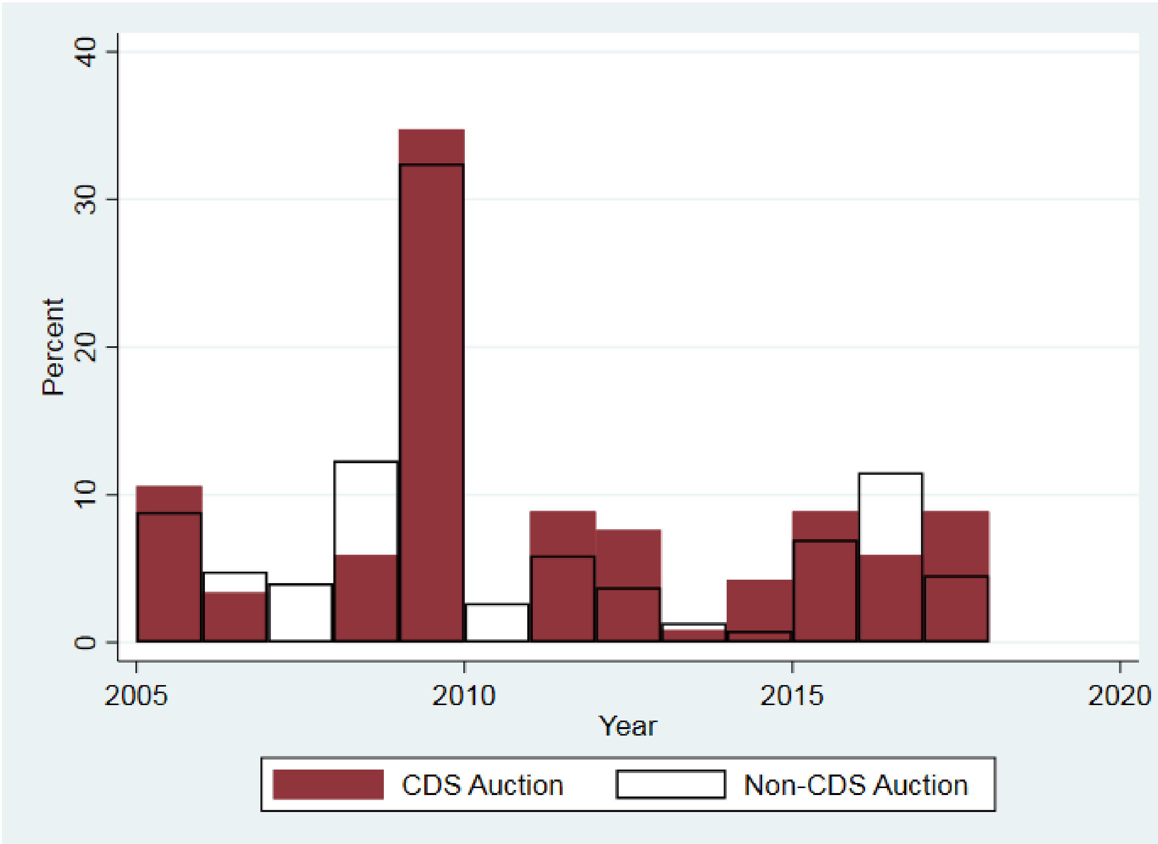

Table 14: Time Fixed-Effects Regression across Time Periods

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	6BDEF YQ	6BDEF Y	6BDEFA YQ	6BDEFA Y	BDEFA YQ	BDEFA Y	12BDEF YQ	12BDEF Y	12BDEFA YQ	12BDEFA Y
CDS Auction	0.671*	0.688**	0.558	0.568*	0.822***	0.364	0.365*	0.362**	0.587**	0.554***
	(1.786)	(2.281)	(1.429)	(1.807)	(3.038)	(1.540)	(1.835)	(2.248)	(2.324)	(2.702)
Rating	0.148*	0.0628	0.166**	0.0717	0.0220	0.0652	0.0883**	0.0473	0.0967**	0.0503
	(1.966)	(1.076)	(2.199)	(1.222)	(0.423)	(1.579)	(2.264)	(1.539)	(2.014)	(1.312)
Maturity	-0.0727**	-0.0687**	-0.0997***	-0.0896***	-0.0151	-0.0206	-0.0300*	-0.0274*	-0.0585***	-0.0547***
	(-2.446)	(-2.455)	(-3.344)	(-3.186)	(-0.776)	(-1.067)	(-1.885)	(-1.809)	(-3.015)	(-2.920)
Age	0.0693	0.0490	0.0952**	0.0811*	-0.0360	-0.0297	-0.00150	-0.0157	0.0186	0.00625
	(1.529)	(1.207)	(2.067)	(1.954)	(-1.080)	(-0.943)	(-0.0639)	(-0.743)	(0.637)	(0.234)
log(Amt)	0.328	0.343	0.341	0.379*	-0.117	-0.124	0.288**	0.289**	0.366**	0.366**
	(1.351)	(1.529)	(1.427)	(1.696)	(-0.686)	(-0.765)	(2.228)	(2.387)	(2.340)	(2.448)
B/A Spread	0.0483	0.0233	0.0329	0.00604	-0.0246	0.0415*	0.0441**	0.0295	0.0369	0.0181
	(1.112)	(0.639)	(0.756)	(0.166)	(-0.593)	(1.769)	(2.037)	(1.579)	(1.377)	(0.776)
Bond Zero	0.0243***	0.0226***	0.0162***	0.0161***	-0.00302	-0.00190	0.0177***	0.0157***	0.0199***	0.0174***
	(4.219)	(4.281)	(3.498)	(3.698)	(-0.875)	(-0.585)	(6.174)	(5.822)	(5.946)	(5.502)
Amihud	3.209	1.834	-13.38	-13.50	39.01***	39.32***	71.63***	70.83***	57.33***	53.26***
	(0.148)	(0.0886)	(-0.582)	(-0.614)	(4.673)	(4.656)	(6.809)	(6.950)	(4.148)	(3.934)
IRC	0.365***	0.355***	0.616***	0.657***	0.233***	0.265***	0.252***	0.227***	0.417***	0.435***
	(3.091)	(3.321)	(6.070)	(7.074)	(7.359)	(8.518)	(2.960)	(2.969)	(4.348)	(4.913)
EBIT/Assets	0.295	0.587	3.202	4.143*	2.252	1.030	-0.691	-0.404	-0.0260	0.524
	(0.105)	(0.249)	(1.163)	(1.794)	(1.031)	(0.501)	(-0.603)	(-0.394)	(-0.0185)	(0.412)
Sales/Assets	-1.811	-1.025	-2.329*	-1.513	-0.0474	0.606	-0.859	-0.619	-1.310	-0.829
	(-1.392)	(-0.959)	(-1.776)	(-1.403)	(-0.0508)	(0.805)	(-1.266)	(-1.092)	(-1.566)	(-1.174)
RE/Assets	-0.538*	-0.368	-0.502*	-0.270	0.144	0.0403	-0.267*	-0.206	-0.334*	-0.239
	(-1.895)	(-1.450)	(-1.752)	(-1.050)	(0.692)	(0.219)	(-1.876)	(-1.579)	(-1.910)	(-1.467)
Leverage	-0.224	-0.151	-0.349*	-0.307*	0.260*	0.0971	-0.0524	-0.0120	-0.0993	-0.0866
	(-1.134)	(-0.906)	(-1.768)	(-1.849)	(1.772)	(0.803)	(-0.523)	(-0.141)	(-0.806)	(-0.816)

log(Assets)	0.00679	-0.0585	-0.0611	-0.147	0.127	0.137	0.0787	0.0268	0.0421	-0.0397
	(0.0443)	(-0.422)	(-0.401)	(-1.069)	(1.211)	(1.409)	(0.986)	(0.365)	(0.437)	(-0.443)
Cash Flow Vol	2.345	0.632	5.119	2.891	12.85**	16.46***	1.081	0.228	2.791	1.992
	(0.326)	(0.102)	(0.699)	(0.459)	(2.364)	(3.499)	(0.293)	(0.0708)	(0.612)	(0.494)
Earnings Vol	-4.554	-2.674	-3.518	-0.939	-1.134	-1.252	-2.595	-1.917	-3.142	-1.862
	(-1.122)	(-0.713)	(-0.855)	(-0.247)	(-0.259)	(-0.322)	(-1.239)	(-0.970)	(-1.212)	(-0.752)
Sales Vol	2.754	0.658	0.632	-0.845	-1.745	-4.506**	2.471	1.079	1.791	-0.304
	(0.734)	(0.209)	(0.166)	(-0.264)	(-0.598)	(-2.003)	(1.252)	(0.640)	(0.732)	(-0.144)
Observations	330	330	331	331	247	247	334	334	335	335
Adjusted R-squared	0.157	0.178	0.275	0.289	0.459	0.406	0.335	0.335	0.326	0.309

*** p<0.01, ** p<0.05, * p<0.1

Reported are the baseline cross-sectional regressions with an added time fixed-effect component across all time periods. YQ represents time fixed-effects by year-quarters and Y by years. All variables are defined as in Table 5. *t-statistics* are shown in parentheses.

Table 15: Time Fixed-Effects Regression across Time Periods (with Clustered Standard Errors)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	6BDEF YQ	6BDEF Y	6BDEFA YQ	6BDEFA Y	BDEFA YQ	BDEFA Y	12BDEF YQ	12BDEF Y	12BDEFA YQ	12BDEFA Y
CDS Auction	0.671	0.688	0.558	0.568	0.822*	0.364	0.365	0.362	0.587	0.554
	(1.319)	(1.190)	(1.150)	(1.106)	(1.903)	(1.227)	(1.266)	(1.159)	(1.291)	(1.193)
Rating	0.148	0.0628	0.166	0.0717	0.0220	0.0652	0.0883	0.0473	0.0967	0.0503
	(1.442)	(1.207)	(1.223)	(1.145)	(0.336)	(0.939)	(1.503)	(1.353)	(1.166)	(1.140)
Maturity	-0.0727	-0.0687	-0.0997	-0.0896	-0.0151	-0.0206	-0.0300	-0.0274	-0.0585	-0.0547
	(-1.106)	(-1.048)	(-1.246)	(-1.163)	(-1.170)	(-1.449)	(-1.113)	(-1.050)	(-1.360)	(-1.224)
Age	0.0693	0.0490	0.0952	0.0811	-0.0360*	-0.0297	-0.00150	-0.0157	0.0186	0.00625
	(1.269)	(1.107)	(1.257)	(1.247)	(-1.720)	(-1.292)	(-0.0690)	(-0.751)	(0.666)	(0.303)
log(Amt)	0.328	0.343	0.341	0.379	-0.117	-0.124	0.288	0.289	0.366	0.366
	(1.257)	(1.236)	(0.948)	(1.131)	(-0.850)	(-0.855)	(1.398)	(1.285)	(1.185)	(1.172)
B/A Spread	0.0483	0.0233	0.0329	0.00604	-0.0246	0.0415	0.0441***	0.0295*	0.0369**	0.0181
	(1.439)	(0.647)	(0.813)	(0.133)	(-0.943)	(1.646)	(2.751)	(1.944)	(2.158)	(0.873)
Bond Zero	0.0243*	0.0226	0.0162	0.0161	-0.00302	-0.00190	0.0177*	0.0157*	0.0199*	0.0174
	(1.789)	(1.645)	(1.557)	(1.502)	(-1.022)	(-0.545)	(1.841)	(1.810)	(1.661)	(1.609)
Amihud	3.209	1.834	-13.38	-13.50	39.01***	39.32***	71.63**	70.83**	57.33**	53.26***
	(0.122)	(0.0708)	(-0.328)	(-0.338)	(5.802)	(8.899)	(2.047)	(2.004)	(2.475)	(2.630)
IRC	0.365*	0.355**	0.616**	0.657**	0.233***	0.265***	0.252***	0.227***	0.417***	0.435***
	(1.777)	(2.229)	(2.402)	(2.343)	(3.325)	(3.760)	(3.081)	(3.902)	(4.115)	(4.768)
EBIT/Assets	0.295	0.587	3.202	4.143	2.252	1.030	-0.691	-0.404	-0.0260	0.524
	(0.152)	(0.310)	(1.312)	(1.355)	(1.064)	(0.495)	(-0.796)	(-0.445)	(-0.0256)	(0.474)
Sales/Assets	-1.811	-1.025	-2.329	-1.513	-0.0474	0.606	-0.859	-0.619	-1.310	-0.829
	(-1.092)	(-1.027)	(-1.336)	(-1.266)	(-0.0525)	(0.830)	(-0.974)	(-1.150)	(-1.217)	(-1.222)
RE/Assets	-0.538	-0.368	-0.502	-0.270	0.144	0.0403	-0.267	-0.206	-0.334	-0.239
	(-1.442)	(-1.243)	(-1.220)	(-0.960)	(1.131)	(0.306)	(-1.369)	(-1.239)	(-1.273)	(-1.107)
Leverage	-0.224	-0.151	-0.349	-0.307	0.260	0.0971	-0.0524	-0.0120	-0.0993	-0.0866

	(-0.935)	(-0.861)	(-1.166)	(-1.240)	(1.562)	(0.632)	(-0.654)	(-0.232)	(-0.829)	(-0.864)
log(Assets)	0.00679	-0.0585	-0.0611	-0.147	0.127	0.137	0.0787	0.0268	0.0421	-0.0397
	(0.0761)	(-0.566)	(-0.543)	(-1.001)	(1.656)	(1.579)	(1.071)	(0.551)	(0.457)	(-0.490)
Cash Flow Vol	2.345	0.632	5.119	2.891	12.85**	16.46***	1.081	0.228	2.791	1.992
	(0.593)	(0.206)	(1.132)	(0.885)	(2.185)	(2.732)	(0.394)	(0.106)	(0.923)	(0.777)
Earnings Vol	-4.554*	-2.674	-3.518	-0.939	-1.134	-1.252	-2.595	-1.917	-3.142	-1.862
	(-1.704)	(-1.326)	(-1.318)	(-0.513)	(-0.278)	(-0.361)	(-1.622)	(-1.387)	(-1.608)	(-1.270)
Sales Vol	2.754	0.658	0.632	-0.845	-1.745	-4.506**	2.471	1.079	1.791	-0.304
	(1.211)	(0.420)	(0.270)	(-0.466)	(-0.655)	(-2.008)	(1.454)	(0.988)	(0.882)	(-0.242)
Observations	330	330	331	331	247	247	334	334	335	335
Adjusted R-squared	0.157	0.178	0.275	0.289	0.459	0.406	0.335	0.335	0.326	0.309

*** p<0.01, ** p<0.05, * p<0.1

Reported are the baseline cross-sectional regressions with an added time fixed-effect component across all time periods. YQ represents time fixed-effects by year-quarters and Y by years. All variables are defined as in Table 5. *t-statistics* are shown in parentheses and use standard errors clustered by firm.

10. Appendix

Table A1: Summary Stats 12BDEF

VARIABLES	Panel A All Bonds N	 mean	 std	Panel B Bonds Not in CDS Auction mean	 std	Panel C Bonds in CDS Auction mean	 Std
Number of Trades	605	1,787	2,756	1,588	2,652	2,104	2,890
Volume Traded	605	571.6	830.3	481	691.2	715.2	997.5
Daily Return	593	-0.00672	0.0364	-0.00331	0.0129	-0.0121	0.0558
Daily Volatility	590	0.0667	0.117	0.0608	0.100	0.0760	0.138
Annual Volatility	590	0.996	1.564	0.861	0.942	1.206	2.197
Rating	496	17.16	2.089	17.13	2.028	17.21	2.232
Bond Zero	605	57.44	28.63	57.37	30.47	57.55	25.51
Age	600	5.820	4.680	4.915	3.662	7.285	5.684
Maturity	600	5.670	6.733	5.251	7.305	6.351	5.635
IRC	601	1.651	1.162	1.580	1.142	1.762	1.188
Amihud	604	0.00613	0.00670	0.00574	0.00668	0.00675	0.00669
SD(IRC)	594	2.447	2.433	2.354	2.546	2.596	2.237
SD(Amihud)	598	0.0156	0.0330	0.0155	0.0399	0.0159	0.0171
Log(Amt)	600	19.81	0.927	19.72	0.825	19.96	1.058
CDS Auction	605	0.387	0.487	0	0	1	0
CDS Firm	605	0.797	0.402	0.682	0.465	0.979	0.145
EBIT/Assets	545	-0.0212	0.108	-0.0211	0.0808	-0.0213	0.142
Coverage Ratio	551	-0.259	8.205	-0.0652	7.859	-0.569	8.739
Sales/Assets	545	0.182	0.143	0.191	0.166	0.167	0.0962
RE/Assets	545	-0.528	0.747	-0.523	0.773	-0.535	0.706
NI/Assets	545	-0.0701	0.126	-0.0698	0.116	-0.0707	0.141
CF/Assets	545	-0.00541	0.0528	0.00423	0.0498	-0.0209	0.0540
Earnings/Assets	544	-0.0690	0.125	-0.0696	0.114	-0.0681	0.140
Leverage	545	0.422	0.849	0.408	0.798	0.444	0.926
Cash Flow Vol	541	0.0361	0.0267	0.0408	0.0268	0.0286	0.0248
Earnings Vol	541	0.0447	0.0460	0.0493	0.0502	0.0373	0.0373
Sales Vol	541	0.0434	0.0519	0.0515	0.0609	0.0305	0.0283
Leverage Vol	541	0.159	0.249	0.151	0.231	0.171	0.277
log(Assets)	545	8.655	1.642	8.111	1.768	9.528	0.881
B/A Spread	470	3.084	4.816	3.117	5.193	3.031	4.158
SD(B/A Spread)	454	0.972	1.834	0.911	1.842	1.067	1.821

Summary statistics for all bonds in my sample (Panel A), bonds not in CDS auction (Panel B), and bonds in CDS auction (Panel C) for time period 12BDEF. Observations are reported at the bond level. All variables are defined as in Table 2.

Table A2: Summary Stats 6BDEFA

	Panel A			Panel B		Panel C	
	All Bonds			Bonds Not in CDS Auction		Bonds in CDS Auction	
VARIABLES	N	mean	std	mean	std	mean	std
Number of Trades	592	1,105	1,829	1,002	1,884	1,267	1,732
Volume Traded	592	363.7	591.5	292	447.1	475.1	751
Daily Return	583	-0.0138	0.0969	-0.00560	0.0580	-0.0263	0.135
Daily Volatility	576	0.0961	0.186	0.0782	0.143	0.123	0.234
Annual Volatility	576	1.398	2.504	1.029	0.995	1.952	3.707
Rating	490	17.13	2.091	17.10	2.032	17.20	2.227
Bond Zero	592	56.52	30.81	56.42	32.06	56.67	28.83
Age	585	5.877	4.734	5.006	3.739	7.270	5.731
Maturity	585	5.726	6.827	5.281	7.443	6.437	5.647
IRC	589	2.328	2.129	1.946	1.796	2.920	2.450
Amihud	592	0.00718	0.0158	0.00606	0.00644	0.00891	0.0238
SD(IRC)	578	3.197	3.547	2.648	3.125	4.052	3.978
SD(Amihud)	585	0.0159	0.0228	0.0153	0.0225	0.0169	0.0234
Log(Amt)	585	19.81	0.917	19.73	0.809	19.95	1.056
CDS Auction	592	0.392	0.489	0	0	1	0
CDS Firm	592	0.799	0.400	0.683	0.464	0.978	0.146
EBIT/Assets	534	-0.0211	0.106	-0.0205	0.0755	-0.0221	0.142
Coverage Ratio	540	-0.309	8.265	-0.110	7.928	-0.621	8.778
Sales/Assets	534	0.184	0.144	0.193	0.167	0.170	0.0967
RE/Assets	534	-0.533	0.751	-0.528	0.776	-0.540	0.712
NI/Assets	534	-0.0692	0.124	-0.0680	0.112	-0.0710	0.142
CF/Assets	534	-0.00652	0.0537	0.00332	0.0505	-0.0221	0.0549
Earnings/Assets	533	-0.0681	0.123	-0.0679	0.111	-0.0685	0.140
Leverage	534	0.428	0.847	0.412	0.793	0.454	0.929
Cash Flow Vol	530	0.0365	0.0268	0.0411	0.0270	0.0292	0.0249
Earnings Vol	530	0.0451	0.0461	0.0497	0.0503	0.0379	0.0375
Sales Vol	530	0.0442	0.0524	0.0522	0.0616	0.0316	0.0290
Leverage Vol	530	0.159	0.248	0.153	0.228	0.170	0.278
log(Assets)	534	8.668	1.636	8.118	1.756	9.537	0.899
B/A Spread	459	3.135	4.966	3.279	5.501	2.909	3.993
SD(B/A Spread)	444	1.009	1.868	0.964	1.924	1.078	1.781

Summary statistics for all bonds in my sample (Panel A), bonds not in CDS auction (Panel B), and bonds in CDS auction (Panel C) for time period 6BDEFA. Observations are reported at the bond level. All variables are defined as in Table 2.

Table A3: Summary Stats BDEF6

	Panel A			Panel B		Panel C	
	All Bonds			Bonds Not in CDS Auction		Bonds in CDS Auction	
VARIABLES	N	mean	std	mean	std	mean	std
Number of Trades	596	939.2	1,573	877.7	1,646	1,035	1,450
Volume Traded	596	305.7	491.1	259.7	398.6	377.4	603.8
Daily Return	585	-0.0187	0.139	-0.00677	0.0574	-0.0370	0.208
Daily Volatility	577	0.0834	0.166	0.0749	0.141	0.0966	0.199
Annual Volatility	577	1.215	2.159	1.008	1.060	1.533	3.159
Rating	488	17.13	2.093	17.11	2.035	17.20	2.227
Bond Zero	596	56.90	28.43	56.27	29.65	57.88	26.45
Age	591	5.830	4.696	4.920	3.666	7.278	5.696
Maturity	591	5.709	6.773	5.290	7.376	6.375	5.636
IRC	591	2.102	1.721	1.921	1.586	2.389	1.883
Amihud	596	0.00639	0.00724	0.00608	0.00669	0.00688	0.00802
SD(IRC)	576	2.813	2.982	2.566	2.968	3.210	2.968
SD(Amihud)	585	0.0149	0.0208	0.0147	0.0213	0.0153	0.0200
Log(Amt)	591	19.83	0.924	19.74	0.817	19.96	1.060
CDS Auction	596	0.391	0.488	0	0	1	0
CDS Firm	596	0.800	0.399	0.686	0.463	0.979	0.145
EBIT/Assets	538	-0.0206	0.106	-0.0200	0.0752	-0.0215	0.142
Coverage Ratio	544	-0.280	8.234	-0.0910	7.891	-0.579	8.759
Sales/Assets	538	0.182	0.144	0.191	0.167	0.168	0.0964
RE/Assets	538	-0.525	0.747	-0.521	0.772	-0.532	0.706
NI/Assets	538	-0.0693	0.124	-0.0686	0.112	-0.0705	0.142
CF/Assets	538	-0.00587	0.0529	0.00377	0.0499	-0.0211	0.0540
Earnings/Assets	537	-0.0683	0.123	-0.0685	0.110	-0.0679	0.140
Leverage	538	0.422	0.846	0.406	0.790	0.446	0.928
Cash Flow Vol	534	0.0363	0.0267	0.0410	0.0268	0.0287	0.0248
Earnings Vol	534	0.0447	0.0460	0.0494	0.0502	0.0373	0.0374
Sales Vol	534	0.0435	0.0521	0.0518	0.0613	0.0306	0.0284
Leverage Vol	534	0.159	0.248	0.151	0.227	0.172	0.278
log(Assets)	538	8.676	1.630	8.139	1.760	9.528	0.883
B/A Spread	465	3.151	5.025	3.228	5.513	3.031	4.158
SD(B/A Spread)	449	0.987	1.891	0.936	1.936	1.067	1.821

Summary statistics for all bonds in my sample (Panel A), bonds not in CDS auction (Panel B), and bonds in CDS auction (Panel C) for time period BDEF6. Observations are reported at the bond level. All variables are defined as in Table 2.

Table A4: Summary Stats DEFA

	Panel A			Panel B		Panel C	
	All Bonds			Bonds Not in CDS Auction		Bonds in CDS Auction	
VARIABLES	N	mean	std	mean	std	mean	std
Number of Trades	554	170.9	294.1	127.5	272.7	234.2	312.9
Volume Traded	554	597.9	121.2	329.8	607.4	989.9	168.1
Daily Return	549	0.00504	0.143	0.0144	0.0961	-0.00846	0.190
Daily Volatility	524	0.0863	0.172	0.0633	0.111	0.119	0.229
Annual Volatility	524	1.304	2.497	0.893	0.960	1.886	3.634
Rating	455	17.11	2.115	17.08	2.064	17.18	2.223
Bond Zero	554	52.93	29.41	55.84	30.95	48.67	26.50
Age	547	5.957	4.790	4.994	3.758	7.410	5.732
Maturity	547	5.831	6.958	5.500	7.667	6.331	5.704
IRC	544	2.894	4.424	2.058	3.679	4.117	5.096
Amihud	554	0.00670	0.0180	0.00608	0.0114	0.00760	0.0248
SD(IRC)	506	2.979	4.634	2.182	3.655	4.129	5.574
SD(Amihud)	529	0.0111	0.0293	0.0112	0.0332	0.0110	0.0227
Log(Amt)	547	19.88	0.923	19.81	0.804	19.99	1.070
CDS Auction	554	0.406	0.492	0	0	1	0
CDS Firm	554	0.807	0.394	0.687	0.463	0.982	0.132
EBIT/Assets	503	-0.0222	0.109	-0.0222	0.0784	-0.0222	0.143
Coverage Ratio	509	-0.566	7.296	-0.537	6.018	-0.609	8.862
Sales/Assets	503	0.181	0.145	0.189	0.169	0.169	0.0969
RE/Assets	503	-0.536	0.750	-0.532	0.777	-0.540	0.711
NI/Assets	503	-0.0703	0.127	-0.0699	0.115	-0.0709	0.143
CF/Assets	503	-0.00694	0.0535	0.00317	0.0512	-0.0218	0.0535
Earnings/Assets	502	-0.0693	0.125	-0.0699	0.114	-0.0683	0.141
Leverage	503	0.440	0.866	0.427	0.818	0.459	0.935
Cash Flow Vol	501	0.0360	0.0266	0.0408	0.0267	0.0289	0.0249
Earnings Vol	501	0.0457	0.0471	0.0510	0.0519	0.0379	0.0378
Sales Vol	501	0.0435	0.0529	0.0518	0.0629	0.0312	0.0293
Leverage Vol	501	0.164	0.253	0.155	0.233	0.176	0.279
log(Assets)	503	8.785	1.593	8.254	1.742	9.563	0.890
B/A Spread	356	2.432	4.368	2.315	4.768	2.602	3.721
SD(B/A Spread)	338	0.770	1.963	0.622	2.016	0.976	1.874

Summary statistics for all bonds in my sample (Panel A), bonds not in CDS auction (Panel B), and bonds in CDS auction (Panel C) for time period DEFA. Observations are reported at the bond level. All variables are defined as in Table 2.

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