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Credit default swaps and debt specialization☆

Brian Clark [a,*], James Donato [b], Bill B. Francis [a]

[a] *Lally School of Management at Rensselaer Polytechnic Institute, 110 8th Street, Troy, NY 12180, United States*
[b] *University of Wisconsin–River Falls, 212C South Hall, 410 S. Third Street, River Falls, WI 54022, United States*

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ABSTRACT

We examine the effect of credit default swaps (CDSs) on debt specialization. We argue that reference firms in CDS contracts, seeking to minimize creditor conflicts and bankruptcy costs, exhibit higher debt concentration than firms on which no CDSs are traded. Our results show that firms engage in greater debt specialization and are more likely to specialize following the inception of CDS trading. Additionally, we find that, while lender concentration in firms increases, the number of bank lenders drops, lead arranger share rises, and the probability that lead arrangers and lenders are repeated increases following the onset of CDS trading. Our results are robust to instrumental variable estimation, propensity-score matching, different model specifications, and different subsamples.

1. Introduction

A credit default swap (CDS) is an insurance contract on debt whereby the CDS buyer pays insurance premiums to the seller, who agrees to reimburse the buyer for losses in the event of default by the reference entity. In the case of a CDS issued on a corporate bond or loan, the obligor is said to be the reference entity in the CDS contract and default is defined as a borrower's failure to make principal and/or interest payments or a reference entity's filing for bankruptcy. In this paper, we examine the relation between CDS contracts and debt specialization to answer the following question: Do reference firms in CDS contracts borrow from fewer debt sources (i.e., specialize or concentrate their debt) or more sources (diversify their debt) and why?

CDS contracts may distort the typical debtor–creditor relationship because of the "empty creditor" problem whereby lenders retain all economic rights associated with lending but become disinterested in exercising those rights because of the outside option provided by CDS protection (Hu and Black, 2008). Empirical work examining the debtor–creditor relationship for CDS firms finds supportive evidence of the empty-creditor problem. For example, Subrahmanyam et al. (2014) find that there is a decline in borrower credit ratings and an increase in the probability that bankruptcy occurs. Danis (2017) observes a reduction in the likelihood that out-of-court debt exchanges occur while Clark et al. (2020) document a lower likelihood that loans are renegotiated successfully. We hypothesize that reference CDS firms, seeking to address the empty-creditor problem, alter the structure of their liabilities and choose to specialize, or concentrate, their debt structures as a mechanism for avoiding conflicts and the costs associated with financial distress.

Bolton and Scharfstein (1996) point out the inherent trade-off that creditors face between minimizing bankruptcy liquidation costs and maximizing the benefits of maintaining a firm as a going concern (i.e., agreeing to restructure debt). For instance, if a firm faces a "liquidity default" (whereby the firm simply lacks the cash flow it needs to service debt), then creditors benefit by maximizing the firm's liquidation value in the event of bankruptcy. Maximizing the liquidation value may however incentivize managers to engage in "strategic default" wherein they file, or threaten to file, for bankruptcy as a means of writing down debt if the benefits outweigh the costs. Bolton and Scharfstein offer debt specialization as a solution to this problematic trade-off. Debt specialization can maximize CDS firms' liquidation value by easing conflicts associated with renegotiating debt or arranging for the sale of a company. For its part, debt diversification can make it less likely that strategic default occurs because a large number of creditors could drive up bankruptcy costs and make liquidation more likely.

Using a sample of 14,127 firm-year observations for 2189 individual firms (239 CDS firms and 1950 non-CDS firms) for the years 2002–2014, we find greater debt concentration in firms after the onset of CDS trading

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* Corresponding author.
E-mail address: clarkb2@rpi.edu (B. Clark).

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than before, as measured by the normalized Herfindahl-Hirschman Index (HHI), our primary measure of debt specialization. This finding is consistent with our argument that CDS firms exhibit higher debt concentration than non-CDS firms as a way to minimize creditor conflicts and bankruptcy costs. Additionally, we find that firms are significantly more likely to concentrate their debt structures after CDS trading on their debt begins. Specifically, we find that, following the initiation of CDS trading, firms borrow from fewer debt sources or hold a higher proportion of a specific debt type as a way of minimizing the number of creditors in bankruptcy, thereby reducing costs and avoiding conflicts. We further extend our analysis beyond debt-structure concentration to include lender-structure concentration and find that, for CDS firms, the number of bank lenders decreases, lender concentration increases, lead arranger share increases, and the presence of repeat lead arrangers and repeat lenders increases following the onset of CDS trading.

In our analysis we assume that debt specialization in fewer types of debt equates to concentration in the number of lenders. Although this assumption is reasonable, it is also possible that concentrating into public, dispersedly owned bond debt would increase the number of creditors and, hence, increase bankruptcy costs. We therefore examine the relation between CDS contracts and the number and concentration of creditors directly using bank loan data and obtain results consistent with our baseline models. Importantly, we find no statistical evidence of a substitution effect from bank debt into public debt for investment-grade firms, which comprise the vast majority of our sample.

Finally, to control for endogeneity between debt specialization and CDS trading, we use two instrumental variables (IVs) that are widely used throughout the CDS literature—*Lender FX Hedging* (Saretto and Tookes, 2013) and *Lender Tier 1 Capital Ratio* (Subrahmanyam et al., 2014; Shan et al., 2014). The results are consistent with our baseline regression results and indicate that a causal relationship between CDS trading and debt specialization exists. We also conduct propensity-score matching (PSM) to control for observable differences between CDS and non-CDS firms and implement a Heckman two-stage model to control for self-selection. In all cases we find results that are similar to those obtained with our baseline specifications.

This paper contributes to several streams of literature. First, we provide evidence pertaining to the role that CDSs play in determining the type and amount of borrowings a firm chooses. Second, by examining the link between CDSs and bank-loan lenders, we demonstrate that CDS trading results in a concentrated lender structure in addition to a concentrated debt structure—a result that until now has not been fully explored in the extant literature. Finally, our results contribute to the empty-creditor literature by providing results consistent with the argument of Hu and Black (2008). To the best of our knowledge, this is the first paper to examine the relation between CDS contracts and debt specialization and to provide robust evidence that there is a positive and causal relationship between the two.

2. Literature review

Previous research examining the impact of CDS contracts on corporate decision-making focuses on the impact of CDSs on financing decisions. Subrahmanyam et al. (2017) show that CDS firms hold higher levels of cash to mitigate the greater bargaining power of empty creditors. Shan and Tang (2013) find that tangible net-worth bank-loan covenants are less stringent following the onset of CDS trading. Narayanan and Uzmanoglu (2018a) show that active CDS trading is associated with lower firm valuation. Danis (2017) shows that bondholders are less likely to participate in out-of-court debt exchanges with distressed CDS firms. Lenders may even adopt net short CDS positions in firms where they become incentivized to force debtors into bankruptcy. Bolton and Oehmke (2011) refer to this phenomenon as over-insurance. Hu and Black (2008) argue that, with the advent of CDS trading, lenders have a weaker incentive to monitor, increasing firms' credit risk. And, finally, Colla et al. (2013) find that the degree of debt specialization is inversely related to credit quality.

Other studies have examined how CDS firms respond to the trading of CDS contracts on their debt. For example, Narayanan and Uzmanoglu (2018b) find that distressed CDS firms are more likely to target junior bondholders, thus increasing the likelihood that they can restructure successfully. Saretto and Tookes (2013) show that CDS firms increase leverage and debt maturity and, using a cross-country survey, Bartram et al. (2022) find that CDS firms in countries with strong legal protections are characterized by increased debt capacity.

In line with our argument, Bris and Welch (2005) contend that multiple claimants (as a result of debt diversification) run the risk of coordination failure but could benefit from higher ex-post payoffs from management as they seek to avoid liquidation. Although less dispersed creditors might be more likely to coordinate around salvaging a firm, they could experience higher debt collection expenses. In contrast, Thadden et al. (2010) theorize that creditor diversification incentivizes firms to seek strategic default. They argue that multiple claimants in a bankruptcy case reduce claims per creditor and, thus, lead to a greater loss of value for debtholders. Ivashina et al. (2016) examine outcomes for US firms in bankruptcy and find evidence supporting the arguments advanced by Bris and Welch (2005) and Thadden et al. (2010). Additionally, consistent with Bolton and Scharfstein (1996), they find that creditor concentration is positively associated with firms that reorganize and emerge from bankruptcy and firms involved in prearranged bankruptcies, but it is negatively associated with time spent in bankruptcy proceedings.

3. Data and methodology

We collect debt-structure data from Capital IQ, annual financial and accounting data from Compustat, bank-loan data from Dealscan, and CDS start data from Bloomberg. Following Colla et al. (2013), we use only firms traded on the NYSE, Amex, and Nasdaq, removing utilities (SIC codes 4900–4999) and financials (SIC codes 6000–6999) because their debt structures are highly regulated. We drop missing or zero-value observations for total assets and total debt, remove all firms with negative equity, and set missing values equal to 0 for research and development expenses. Like Lemmon et al. (2008), we drop firm-year observations that fall outside the unit interval for book leverage. Finally, we merge leveraged firms from Compustat with Bloomberg, Capital IQ, and Dealscan data, and use the link file provided by Chava and Roberts (2008) to merge Dealscan data with Compustat data through the unique identifier, Global Vantage Key.

Our final dataset consists of 14,127 firm-year observations for 2189 individual firms (239 CDS and 1950 non-CDS firms) for the years 2002–2014. The sample period begins in 2002 because Capital IQ data are comprehensive beginning in 2002 (see Colla et al., 2013), which also coincides with the start of the bulk of CDS trading. Of our total firm-year observations, 11,571 involve non-CDS firms and 2556 involve CDS firms (651 *before* and 1905 *after* the start of CDS trading).

Following Colla et al. (2013), we construct two measures of debt specialization. The first is the normalized *HHI*, defined as follows,

$$HHI_{i,t} = \frac{SS_{i,t} - \frac{1}{7}}{1 - \frac{1}{7}}, \tag{1}$$

where $SS_{i,t}$ is the sum of squared debt ratios defined as

$$SS_{i,t} = \left(\frac{CP_{i,t}}{TD_{i,t}}\right)^2 + \left(\frac{DC_{i,t}}{TD_{i,t}}\right)^2 + \left(\frac{TL_{i,t}}{TD_{i,t}}\right)^2 + \left(\frac{SBN_{i,t}}{TD_{i,t}}\right)^2 + \left(\frac{SUB_{i,t}}{TD_{i,t}}\right)^2 + \left(\frac{CL_{i,t}}{TD_{i,t}}\right)^2 + \left(\frac{Other_{i,t}}{TD_{i,t}}\right)^2. \tag{2}$$

CP is commercial paper, *DC* is drawn credit (revolving credit facilities), *TL* is term loans, *SBN* is senior bonds and notes, *SUB* is

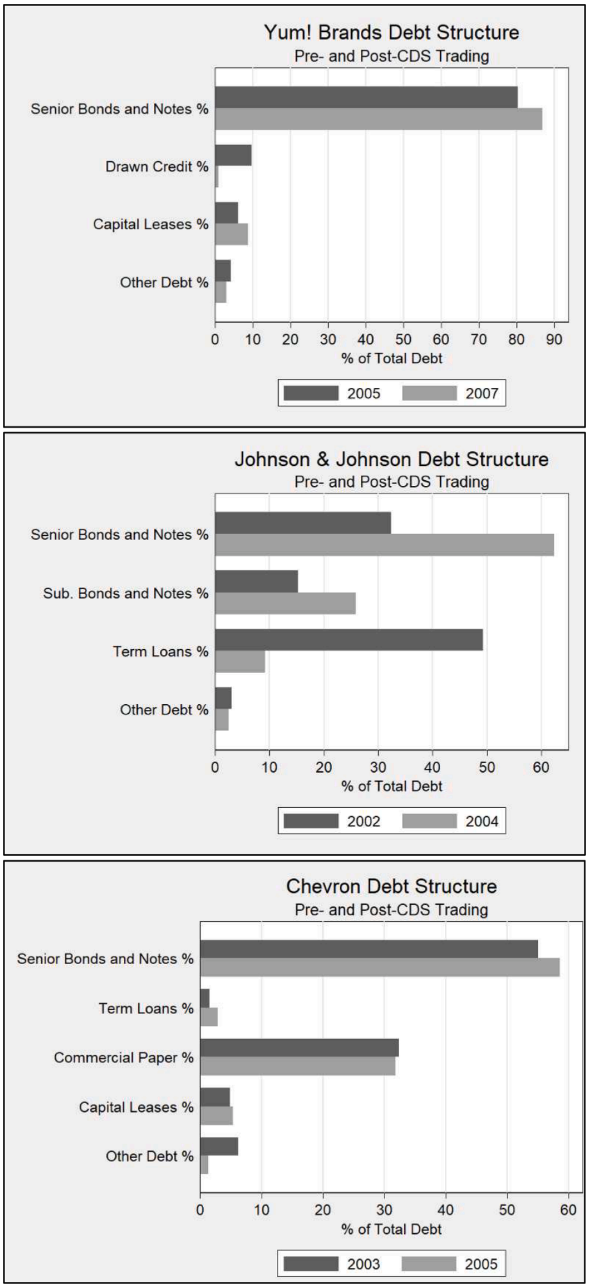

Fig. 1. This figure illustrates debt structure before and after the inception of CDS trading. The percentage of total debt is indicated on the horizontal axis while pre- and post-CDS trading years (by debt category) are indicated on the vertical axis. CDSs began trading on Yum! Brands debt in 2006, Johnson & Johnson debt in 2003, and Chevron debt in 2004.

subordinated bonds and notes, *CL* is capital leases, *Other* is all other debt types plus total trust-preferred stock, and *TD* is total debt. All data for debt-structure variables are drawn from Capital IQ, with the exception of data for *TD*, which is drawn from Compustat. Although Compustat contains data for many of these same variables, Capital IQ has the advantage that all debt-structure variables are self-contained while many of the Compustat versions of those identically named variables appear to overlap. To harmonize the two datasets, we drop observations where the difference between total debt as reported by Compustat and the sum of the seven debt types from Capital IQ is greater than 10%. Grouping the various types of borrowing into these seven distinct categories arguably best captures the chief sources of financing for most firms (i.e., balance-sheet debt used by nonfinancial firms). *HHI* provides

Table A.1
Description of Variables This table lists detailed descriptions of variables used in the paper. Debt structure data are drawn from Capital IQ, annual financial and accounting data are drawn from Compustat, bank-loan data are drawn from Dealscan, and CDS start dates are drawn from Bloomberg.

Dependent Variable	Definition
HHI	Normalized Herfindahl-Hirschman Index defined as $HHI_{i,\,t} = \dfrac{SS_{i,\,t} - \frac{1}{7}}{1 - \frac{1}{7}}$, where $SS_{i,t}$ is the sum of squared debt ratios, $SS_{i,\,t} = \left(\frac{CP_{i,\,t}}{TD_{i,\,t}}\right)^2 + \left(\frac{DC_{i,\,t}}{TD_{i,\,t}}\right)^2 + \left(\frac{TL_{i,\,t}}{TD_{i,\,t}}\right)^2 + \left(\frac{SBN_{i,\,t}}{TD_{i,\,t}}\right)^2 + \left(\frac{SUB_{i,\,t}}{TD_{i,\,t}}\right)^2 + \left(\frac{CL_{i,\,t}}{TD_{i,\,t}}\right)^2 + \left(\frac{Other_{i,\,t}}{TD_{i,\,t}}\right)^2$, where *CP* is commercial paper, *DC* is drawn credit (revolving credit facilities), *TL* is term loans, *SBN* is senior bonds and notes, *SUB* is subordinated bonds and notes, *CL* is capital leases, *Other* is all other debt types plus total trust-preferred stock, and *TD* is total debt.
Excl90, Excl80, Excl70, Excl60	Indicator variable that equals one if any debt type is a certain% or greater of total debt and zero otherwise.
HHI_Lenders	Normalized Herfindahl-Hirschman Index of bank-lender loan ownership.
NumLenders	Natural logarithm of the number of unique bank lenders per firm per year.
LeadArrShare	Percentage of bank loans owned by a lead arranger.
RepeatLender	Indicator variable that equals one if a firm has at least one repeat bank lender in a given firm-year and zero otherwise.
RepeatLeadArr	Indicator variable that equals one if a firm has at least one repeat bank lead arranger in a given firm-year and zero otherwise.
BankDebt	Term loans and drawn credit as a% of total debt.
PublicDebt	Senior bonds and notes, subordinated bonds and notes, and commercial paper as a% of total debt.
Variable of Interest	Definition
CDS_Active	Indicator variable that equals one when a CDS contract begins trading on a firm's debt and continues doing so thereafter.
Instrumental Variable	Definition
Lender Tier 1 Capital Ratio	Average Tier 1 Capital Ratio of a firm's bank lenders in a given year.
Lender FX Hedging	Average foreign exchange hedging of a firm's bank lenders, scaled by total assets per bank.
Control Variable	Definition
CDS_Firm	Indicator variable that equals one if a firm experiences a CDS traded at any point in the sample period.
lnSize	Log of total assets deflated to millions of 2002 dollars.
MktBk	Market capitalization plus total debt plus preferred stock-liquidating value minus deferred taxes and investment tax credit scaled by total assets.
Profitability	Operating income before depreciation divided by total assets.
DivPayer	Indicator variable that equals one if common stock dividends are positive and zero otherwise.
Tangibility	Total net property, plant, and equipment scaled by total assets.
CFvol	Standard deviation of quarterly *Profitability* using the immediately preceding twelve quarters and averaged per year.
RDexp	Research and development expenses divided by total assets.
Unrated	Indicator variable that equals one if a firm is not rated by S&P and zero otherwise.
BookLev	Total debt scaled by total assets.
Issuance	Indicator variable that equals one if a firm issues either long-term bonds and notes or takes out bank loans in a given year.

a measure of concentration by debt size as a proportion of the total amount of debt and ranges from zero (where debt is equal across all seven debt types) to one (where there is only one type of debt), inclusive. We normalize *HHI* to ensure that the lower bound will be zero. However,

Table 1

Descriptive Statistics This table presents descriptive statistics for all variables used in the paper (defined in Table A.1). All continuous control variables are winsorized at the 1% and 99% levels. The dataset consists of 14,127 firm-year observations with 2189 individual firms (239 CDS and 1950 non-CDS firms) for the years 2002–2014. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Full Sample

	Mean	Std. Dev.	1st Pct.	25th Pct.	Median	75th Pct.	99th Pct.
HHI	0.699	0.256	0.204	0.457	0.720	0.975	1.000
Excl90	0.446	0.497	0.000	0.000	0.000	1.000	1.000
Excl80	0.577	0.494	0.000	0.000	1.000	1.000	1.000
Excl70	0.699	0.459	0.000	0.000	1.000	1.000	1.000
Excl60	0.819	0.385	0.000	1.000	1.000	1.000	1.000
CDS_Active	0.135	0.342	0.000	0.000	0.000	0.000	1.000
CDS_Firm	0.181	0.385	0.000	0.000	0.000	0.000	1.000
Total Assets (mill.)	4102.3	8994.2	8.558	218.8	892.3	3296.9	55,651
MktBk	1.594	1.503	0.321	0.823	1.175	1.804	7.558
Profitability	0.082	0.241	-0.880	0.068	0.118	0.167	0.376
DivPayer	0.410	0.492	0.000	0.000	0.000	1.000	1.000
Tangibility	0.292	0.241	0.007	0.099	0.218	0.426	0.910
CFvol	0.021	0.036	0.002	0.006	0.011	0.021	0.216
RDexp	0.042	0.137	0.000	0.000	0.000	0.028	0.616
Unrated	0.573	0.495	0.000	0.000	1.000	1.000	1.000
BookLev	0.262	0.198	0.000	0.108	0.233	0.374	0.852

Panel B: CDS versus Non-CDS Firms

	CDS Firms			Non-CDS Firms			Paired T-Test	Wilcoxon Test
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Difference	|z|
HHI	0.677	0.707	0.240	0.703	0.725	0.260	-0.026***	7.743***
Excl90	0.406	0.000	0.491	0.455	0.000	0.498	-0.049***	4.554***
Excl80	0.588	1.000	0.492	0.575	1.000	0.494	0.013	1.213
Excl70	0.732	1.000	0.443	0.692	1.000	0.462	0.040***	4.026***
Excl60	0.849	1.000	0.358	0.812	1.000	0.391	0.037***	4.369***
Total Assets (mill.)	15,610.8	9098.0	15,325.1	1560.1	590.2	3343.6	14,050.7***	70.755***
MktBk	1.390	1.141	0.892	1.639	1.183	1.603	-0.249***	3.688***
Profitability	0.142	0.140	0.067	0.069	0.112	0.262	0.073***	17.376***
DivPayer	0.755	1.000	0.430	0.333	0.000	0.471	0.422***	39.230***
Tangibility	0.324	0.299	0.214	0.284	0.201	0.246	0.040***	12.412***
CFvol	0.011	0.007	0.012	0.023	0.012	0.039	-0.012***	25.380***
RDexp	0.014	0.000	0.025	0.048	0.000	0.150	-0.034***	3.380***
Unrated	0.011	0.000	0.104	0.697	1.000	0.460	-0.686***	63.465***
BookLev	0.307	0.273	0.167	0.252	0.220	0.203	0.055***	16.708***

Table 2

Debt Specialization (HHI) & CDSs Over Time Panel A provides summary data for a period running before and after the 2008 financial crisis. Data reported in Panel B represent the full sample of firms in the dataset while Panel C data represent only the subsample of CDS firms. For t-tests, ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Summary for HHI

	Full Sample	Pre-Crisis	Post-Crisis	*Difference*
Avg. HHI	0.699	0.689	0.707	0.018***
Avg. HHI (CDS Firms)	0.677	0.639	0.723	0.084***
Avg. HHI (Non-CDS Firms)	0.703	0.702	0.705	0.003
Difference	-0.026***	-0.063***	0.018**	
Avg. HHI (Post-CDS Trading)	0.704	0.668	0.729	0.061***
Avg. HHI (Pre-CDS Trading)	0.599	0.602	0.560	-0.042
Difference	0.105***	0.066***	0.169***	

Panel B: HHI of CDS vs. Non-CDS Firms

	Year												
CDS_Firm	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
1	0.622	0.661	0.687	0.639	0.628	0.618	0.621	0.716	0.725	0.702	0.735	0.738	0.720
0	0.686	0.704	0.702	0.703	0.710	0.713	0.693	0.710	0.713	0.707	0.709	0.702	0.690
Difference	-0.064***	-0.043**	-0.015	-0.064***	-0.082***	-0.095***	-0.072***	0.006	0.012	-0.005	0.026	0.036*	0.030

Panel C: HHI Before & After Onset of CDS Trading (Sub-sample of CDS Firms)

	Year												
CDS_Active	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
1	0.690	0.752	0.718	0.678	0.651	0.631	0.627	0.731	0.733	0.712	0.741	0.738	0.720
0	0.602	0.581	0.653	0.594	0.601	0.581	0.560	0.531	0.594	0.483	0.629		
Difference	0.088**	0.171***	0.065*	0.084**	0.050	0.050	0.067	0.200***	0.139*	0.229***	0.112		

the sample includes only leveraged firms with *HHI* greater than zero.

The second set of debt-specialization measures is a series of dummy variables. For example, we construct a dummy variable, *Excl90*, that equals 1 if any debt type comprises 90% or greater of total debt and 0 otherwise (see, e.g., Colla et al., 2013). We define the variables *Excl80, Excl70*, and *Excl60* in the same fashion for firms that rely primarily on one type of debt.

The key independent variable of interest is *CDS_Active*, which is a

Table 3

Multivariate Regressions on Debt Specialization (HHI) & CDS Trading For this table we test the effects of the onset of CDS trading and traditional determinants of capital structure on debt specialization. The dependent variable is *HHI* (Herfindahl-Hirschman Index). All right-hand-side variables are lagged except for *CDS_Firm*. *CDS_Active* is the main variable of interest and equals one (zero otherwise) when a CDS contract begins trading on a firm's debt and continues doing so thereafter. All continuous control variables are winsorized at the 1% and 99% levels. All models include Fama-French 48 industry and year fixed effects. Robust standard errors are in reported parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The CDS subsample (columns 4–6) is restricted to include only firms that have at least on CDS contract traded on their debt at any point in the sample period.

	Full Sample			CDS Subsample		
	(1)	(2)	(3)	(4)	(5)	(6)
	HHI	HHI	HHI	HHI	HHI	HHI
CDS_Active	0.022***	0.103***	0.133***	0.082***	0.071***	0.102***
	(0.007)	(0.011)	(0.015)	(0.013)	(0.014)	(0.021)
CDS_Firm		-0.000	-0.001			
		(0.011)	(0.011)			
lnSize		-0.018***	-0.018***		-0.012**	-0.011*
		(0.002)	(0.002)		(0.006)	(0.006)
MktBk		0.013***	0.013***		-0.025***	-0.025***
		(0.002)	(0.002)		(0.007)	(0.007)
Profitability		0.147***	0.147***		0.233***	0.238***
		(0.022)	(0.022)		(0.085)	(0.084)
DivPayer		0.005	0.004		0.062***	0.060***
		(0.006)	(0.006)		(0.013)	(0.013)
Tangibility		-0.054***	-0.045***		-0.095***	-0.040
		(0.015)	(0.015)		(0.036)	(0.044)
CFvol		0.474***	0.474***		0.858**	0.867**
		(0.110)	(0.109)		(0.421)	(0.417)
Rdexp		0.278***	0.280***		0.160	0.152
		(0.043)	(0.044)		(0.316)	(0.315)
Unrated		0.030***	0.030***		0.122**	0.122**
		(0.008)	(0.008)		(0.055)	(0.055)
BookLev		-0.385***	-0.385***		-0.213***	-0.214***
		(0.015)	(0.015)		(0.036)	(0.036)
CDS_Active X			-0.090***			-0.091**
Tangibility			(0.029)			(0.044)
Constant	0.794***	0.967***	0.960***	0.760***	0.821***	0.795***
	(0.044)	(0.041)	(0.041)	(0.082)	(0.117)	(0.117)
N	11,295	11,295	11,295	2350	2350	2350
Model	Tobit	Tobit	Tobit	Tobit	Tobit	Tobit
F statistic	12.87***	35.07***	34.82***	30.26***	31.1***	26.21***
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

dummy variable that equals 1 when a CDS contract begins trading on a firm's debt and continues doing so thereafter. For non-CDS firms, *CDS_Active* always equals 0. We require CDS firms to have an observation for at least one year before and one year after the year of CDS inception (i.e., if the firm does not have at least −1 and +1 years around the event year, we remove the firm from the sample). *CDS_Firm* is an indicator variable that equals 1 if a firm has a CDS traded at any point in the sample period. Following Ashcraft and Santos (2009) and Saretto and Tookes (2013), we include *CDS_Firm* to control for time-invariant unobservable differences between CDS firms and non-CDS firms.

We also include several variables to control for determinants of capital structure. ln*Size* is the log of total assets deflated to millions of 2002 dollars. We use *MktBk* as a proxy variable for growth opportunities that is measured as the sum of market capitalization, total debt, preferred stock liquidating value minus deferred taxes, and investment tax credit, scaled by total assets. *Profitability* is operating income before depreciation divided by total assets. *DivPayer* is a dummy variable that equals 1 if common stock dividends are positive and 0 otherwise. *Tangibility* and *CFvol* are proxies for bankruptcy costs (Titman and Wessels, 1988; Rajan and Zingales, 1995). *Tangibility* is total net property, plant, and equipment scaled by total assets. *CFvol* is the standard deviation of quarterly *Profitability* using the preceding 12 quarters and averaged per year. Following Sufi (2007), we proxy information opaqueness and monitoring costs with the variable *RDexp*, which is research and development expenses divided by total assets. *Unrated* is a dummy variable that equals 1 if a firm is not rated by S&P and 0 otherwise. *BookLev* is total debt scaled by total assets. We winsorize all continuous control variables at the 1% and 99% levels. Finally, all models include Fama-French 48 industry dummy variables and year fixed effects. All variables used in the paper are defined in Appendix Table A.1.

4. Empirical results

To facilitate our understanding of how debt structure changes after the inception of CDS trading, we provide several examples of such changes in Fig. 1. Consider the following three firms where each increases debt concentration between pre- and post-CDS trading. In the year prior to CDS trading, Yum! Brands (Ticker: YUM) exhibits an *HHI* of 0.604, which increases to 0.725 the year following CDS trading; similarly, total debt increases from $1.86 billion to $3.21 billion. Note also that the firm swaps out of bank debt (drawn credit) into senior bonds and notes. We also observe that for Johnson & Johnson (JNJ) *HHI* increases from 0.267 to 0.376; however, total debt drops, from $4.14 billion to $2.85 billion, as the firm reduces its term-loan bank debt and increases bonds and notes (both senior and subordinated). In contrast, Chevron (CVX) offers mixed effects. Whereas the firm's debt-structure concentration rises from 0.317 to 0.357 between pre- and post-CDS trading, total debt increases marginally from $12.60 billion to $12.87 billion. We also see that Chevron increases both senior bonds and notes (public debt) and term loans (bank debt) while reducing other forms of debt, although the overall mix does not change significantly.

Table 1, Panel A provides univariate statistics for the variables used in our regressions. The reported results indicate a high degree of debt specialization across firms, with a mean *HHI* of 0.699, which is consistent with Colla et al. (2013). We find a similar result with the second specialization measure, the values of which range from 0.446 for *Excl90* to 0.819 for *Excl60*. Approximately 13.5% of the sample represents

Table 4

Bank Lenders, Debt Ownership Concentration, Lead Arrangers & CDS Trading For this table we test the effects of the onset of CDS trading and traditional determinants of capital structure on bank-lender variables as defined in the Data & Methodology section (and Table A.1). All right-hand-side variables are lagged except for *CDS_Firm. CDS_Active* is the main variable of interest and equals one (zero otherwise) when a CDS contract begins trading on a firm's debt and continues doing so thereafter. All continuous control variables are winsorized at the 1% and 99% levels. All models include Fama-French 48 industry and year fixed effects and loan type (term loan, revolver, 364-day facility, other) and loan purpose (corporate purposes, debt repayment, leveraged buyout/management buyout, takeover, working capital, commercial paper backup, acquisition line, other) controls. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) HHI_Lenders	(2) NumLenders	(3) LeadArrShare	(4) RepeatLender	(5) RepeatLeadArr
CDS_Active	0.035***	-0.127***	0.041***	1.962***	2.096***
	(0.011)	(0.031)	(0.011)	(0.706)	(0.699)
CDS_Firm	0.014	-0.081***	0.031***	-0.912***	-0.907***
	(0.009)	(0.024)	(0.008)	(0.273)	(0.263)
lnSize	-0.053***	0.281***	-0.061***	-0.007	-0.014
	(0.004)	(0.008)	(0.004)	(0.075)	(0.074)
MktBk	-0.009**	-0.048***	-0.006	-0.119**	-0.104*
	(0.004)	(0.009)	(0.004)	(0.059)	(0.058)
Profitability	-0.089**	0.883***	-0.106**	-0.018	-0.020
	(0.044)	(0.102)	(0.043)	(0.679)	(0.664)
DivPayer	-0.053***	0.122***	-0.052***	0.028	0.003
	(0.006)	(0.014)	(0.006)	(0.163)	(0.159)
Tangibility	-0.012	-0.053	0.020	0.068	0.059
	(0.018)	(0.043)	(0.017)	(0.406)	(0.393)
CFvol	-0.114	0.086	0.106	1.224	2.084
	(0.228)	(0.371)	(0.239)	(3.896)	(3.963)
RDexp	-0.120	-0.911***	-0.111	-0.289	-0.358
	(0.146)	(0.201)	(0.125)	(1.142)	(1.117)
Unrated	0.020***	-0.151***	0.026***	-0.202	-0.195
	(0.007)	(0.017)	(0.007)	(0.199)	(0.194)
BookLev	0.074***	0.334***	0.051**	0.158	0.165
	(0.022)	(0.042)	(0.020)	(0.443)	(0.428)
CDS_Active X	-0.021	-0.093	-0.050**	-1.007	-0.966
Tangibility	(0.020)	(0.061)	(0.020)	(1.406)	(1.407)
Constant	0.670***	0.062	0.740***	-0.259	-0.196
	(0.058)	(0.139)	(0.042)	(0.790)	(0.775)
N	4334	8064	4289	7862	7862
Model	Tobit	OLS	OLS	Logit	Logit
F statistic	24.77***	-	-	-	-
R-squared	-	0.725	0.425	-	-
Adj. R-squared	-	0.722	0.414	-	-
Pseudo R-squared	-	-	-	0.291	0.282
Avg. Marginal Effect	-	-	-	6.54%	7.35%
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Loan Type Controls	Yes	Yes	Yes	Yes	Yes
Loan Purpose Controls	Yes	Yes	Yes	Yes	Yes

firm-year observations when a CDS contract is trading; 18.1% of the sample is comprised of observations for CDS firms; 41.0% of observations correspond to firms paying dividends; and 57.3% of firm-years involve unrated firms. Although the mean is $4102.31 million, the median of *Total Assets* is only $892.31 million.

In Table 1, Panel B we report results facilitating a comparison of CDS with non-CDS firms. The summary statistics indicate that CDS and non-CDS firms are significantly different. For example, CDS firms are approximately $14.05 billion larger than their non-CDS counterparts, hold greater volumes in tangible assets on their balance sheets (32.4% vs. 28.4%), are considerably more profitable (14.2% vs. 6.9%), and are more highly levered (30.7% vs. 25.2%). In our analysis below, we account for these differences using PSM.

Our main hypothesis is that CDS firms exhibit a higher degree of debt specialization. We contend that this is the case because CDS firms are more likely to declare bankruptcy as a result of the empty-creditor problem (Subrahmanyam et al., 2014). We expect CDS firms to mitigate this increased risk by minimizing the number of creditors with which they would need to negotiate if bankruptcy were to occur. In so doing, CDS firms are more likely to restructure their debt or arrange asset sales but less likely to liquidate (Bolton and Scharfstein, 1996).

Debt specialization can, however, occur in either of two ways. First, firms can specialize simply by employing fewer debt types on the assumption that fewer debt types equate to fewer creditors, which admittedly may not always be the case. For example, a firm may concentrate debt from three types into two while rolling over creditors from the third type into the other two, thus keeping the number of creditors constant. This scenario appears unlikely given that many investors avoid swapping one form of debt for another. Also, many firms rely on a combination of corporate bonds and bank debt. It is doubtful that, as firms concentrate into a higher proportion of senior and subordinated bonds and notes following the onset of CDS trading (as is the case in our sample), bank creditors will (or can) switch their lending from revolving credit lines to corporate bonds. In short, our assumption that fewer debt types lead to fewer creditors appears sound. Second, firms can specialize by holding a higher proportion of one type of debt in comparison with another. For example, a firm's debt structure may consist initially of 50% bonds and notes and 50% bank debt. Following the onset of CDS trading, debt structure changes to 70% bonds and notes and 30% bank debt. In this scenario, a firm is specialized because bondholders now capture a greater percentage of total debt than previously. Ivashina et al. (2016) make use of this idea when they measure creditor concentration as the top ten creditors' percentage of a total claim in bankruptcy.

Table 2 provides evidence consistent with the above argument. As noted above, the average *HHI* is 0.699 for the full sample. When broken

Table 5

Summary Results for Propensity Score Matching This table provides summary results obtained through propensity-score matching of CDS firms and non-CDS firms based on firm-level characteristics. Column 1 displays the results of the regression used to generate propensity scores (marginal effects are detailed in column 2). Columns 3 and 4 display the results of regressions run on the matched sample for *HHI* (Herfindahl-Hirschman Index). All right-hand-side variables are lagged. *CDS_Active* is the main variable of interest and equals one (zero otherwise) when a CDS contract begins trading on a firm's debt and continues doing so thereafter. All continuous control variables are winsorized at the 1% and 99% levels. All models include Fama-French 48 industry and year fixed effects. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Propensity Score Matching Method		Baseline Regressions on Matched Sample	
	(1) CDS_Active	(2) Marginal Effects	(3) HHI	(4) HHI
CDS_Active			0.083***	0.133***
			(0.007)	(0.014)
lnSize	1.054***	0.099***		-0.006
	(0.031)	(0.002)		(0.004)
MktBk	-0.289***	-0.027***		-0.003
	(0.039)	(0.004)		(0.007)
Profitability	1.190***	0.112***		0.222***
	(0.419)	(0.039)		(0.069)
DivPayer	0.537***	0.050***		0.035***
	(0.056)	(0.005)		(0.009)
Tangibility	0.691***	0.065***		0.029
	(0.166)	(0.015)		(0.025)
CFvol	1.768	0.166		0.130
	(1.593)	(0.149)		(0.273)
RDexp	2.005*	0.188*		0.543***
	(1.134)	(0.106)		(0.207)
Unrated	-1.454***	-0.136***		0.066***
	(0.149)	(0.013)		(0.023)
BookLev	0.099	0.009		-0.350***
	(0.172)	(0.016)		(0.024)
CDS_Active X Tangibility				-0.140***
				(0.034)
Constant	-10.380***		0.725***	0.747***
	(0.401)		(0.068)	(0.082)
N	11,111		4700	4700
Model	Probit		Tobit	Tobit
Pseudo R-squared	0.619		-	-
F statistic	-		22.38***	27.52***
Industry FE	Yes		Yes	Yes
Year FE	Yes		Yes	Yes

down into CDS and non-CDS firms, however, we see mean debt specialization of 0.703 in non-CDS firms versus 0.677 in CDS firms, a difference that is significant at the 1% level. This may appear to be inconsistent with our hypothesis, but it should be noted that more highly rated firms (i.e., CDS firms) not only have the benefit of access to public corporate bond markets but also tend to adopt diversified debt structures to minimize the risk of strategic default for their creditors (Bolton and Scharfstein, 1996). More importantly, when we restrict the sample to CDS firms only (i.e., firms that have entered CDS contracts traded on their debt at any time during the sample period), we find results that support our hypothesis. Specifically, prior to the onset of CDS trading, CDS firms have an average *HHI* of 0.599, which increases to 0.704 following the onset of trading. A paired *t*-test indicates that the difference is significant at the 1% level. This difference in means between pre- and post-CDS trading is striking and provides strong support for our hypothesis that the onset of CDS trading increases debt-structure specialization.

4.1. Debt specialization and CDSs

Table 3 presents the results of multivariate regressions we used to test whether the onset of CDS trading impacts debt structure. Specifically, we fit Tobit models by regressing *CDS_Active* and determinants of capital structure on *HHI*. We use Tobit regressions because the dependent variable for debt specialization, *HHI*, is bounded by the unit interval, inclusive.[1] Results reported in columns (1)–(3) correspond to our full sample while those reported in columns (4)–(6) are for the subsample of CDS firms only (i.e., firms that have CDS contracts traded at some point in the dataset).

Our results show that CDS trading affects debt structure through greater specialization. Importantly, the main variable of interest, *CDS_Active*, is both economically and statistically significant in all specifications. For example, in column (3), the coefficient on *CDS_Active* is 0.133, which indicates that, following the inception of CDS trading, debt concentration increases considerably. This result is even more pronounced given the collinearity between *CDS_Active* and *CDS_Firm* (with a correlation of 0.787), which runs the risk of inflating standard errors, thus leading to a false negative. Further, to demonstrate that firms with fully concentrated debt structures (i.e., total debt consisting of only one type) are not driving our results, we rerun the regressions associated with Table 3 while excluding firms with *HHI* equal to 1 (100%) and find similar results. We repeat this process with firms with *HHI* greater than or equal to 0.90 (90%) and find consistent outcomes as well. (These results and all others not presented in the text of the paper, the Appendix, or Internet Supplementary Material are available upon request.)

Our control variable results are generally significant with intuitively correct signs and consistent with findings reported in the existing literature. For example, the coefficient on *Unrated* is positive, suggesting that debt in firms that are not rated by S&P are more highly specialized because they lack access to public bond markets and face higher credit risk. We explore this issue further in subsequent analyses with subsamples of rated, investment-grade, and below-investment-grade firms. *BookLev* is strongly negative, indicating that as firms increase their debt load they diversify their debt structures. The coefficient on ln*Size* is negative, which may reflect the fact that, as firms grow, they gain access to additional financing options and find concentration of debt structure less necessary. We proxy for information opaqueness and monitoring costs with the variable *RDexp*, which yields a statistically significant and economically meaningful estimate. This is consistent with the argument (e.g., Sufi, 2007) that, as firms increase research and development, they become increasingly difficult to value because much of the value is conditional on unrealized gains. We use *Tangibility* and *CFvol* to proxy for bankruptcy costs (Titman and Wessels, 1988; Rajan and Zingales, 1995) and find, consistent with our expectations, that *Tangibility* is negatively related to debt specialization while *CFvol* is positively correlated with debt specialization. Note that we also include the interaction between *CDS_Active* and *Tangibility* because both are linked to bankruptcy—CDS trading increases the probability that bankruptcy occurs, while tangible assets serve as a proxy for bankruptcy costs—and help to explain the variance in *HHI*. The coefficient, which is negative and significant, further accentuates the effect of *Tangibility*.

In Table 3, columns (4)–(6), using a more direct test, we present evidence indicating whether the onset of CDS trading affects debt specialization. Specifically, we restrict the sample to include only those firms with CDS contracts traded on their debt at any point in our sample period. By creating a subsample consisting of CDS firms only, we can better identify ex-ante and ex-post changes in debt structure. The results are striking. In all regression models, the coefficient on *CDS_Active* is economically and statistically significant. In fact, the coefficient has a consistent magnitude for all model specifications, ranging from 8.24% (column (4)) to 10.16% (column (6)). A number of controls lack significance, which may reflect the small sample size. Likewise, *Unrated* has the opposite sign of what we would expect, which may be a product of

[1] For robustness purposes, we reran all Tobit regressions using ordinary least squares (OLS) models and obtained similar results.

Table 6
Instrumental Variable Estimation For this table we test the effects of the onset of CDS trading and traditional determinants of capital structure on debt specialization. The dependent variable is *HHI* (Herfindahl-Hirschman Index). All right-hand-side variables are lagged. *CDS_Active_Instrumented* is the main variable of interest and equals one (zero otherwise) when a CDS contract begins trading on a firm's debt and continues doing so thereafter. *CDS_Active* is instrumented with bank-lender foreign exchange hedging (columns (1) – (4)) and the bank-lender tier one capital ratio (columns (5)–(8)). All continuous control variables are winsorized at the 1% and 99% levels. All models include Fama-French 48 industry fixed effects. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Lender FX Hedging IV				Lender Tier 1 Capital Ratio IV			
	Full Sample		CDS Subsample		Full Sample		CDS Subsample	
	3 Year Avg.	5 Year Avg.	3 Year Avg.	5 Year Avg.	3 Year Avg.	5 Year Avg.	3 Year Avg.	5 Year Avg.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	HHI	HHI	HHI	HHI	HHI	HHI	HHI	HHI
CDS_Active_Instrumented	0.380***	0.406***	0.167***	0.154***	0.419***	0.568***	0.189***	0.191***
	(0.138)	(0.118)	(0.027)	(0.026)	(0.126)	(0.182)	(0.026)	(0.028)
lnSize	-0.063***	-0.068***	-0.017**	-0.016**	-0.068***	-0.092***	-0.020***	-0.021***
	(0.023)	(0.019)	(0.007)	(0.007)	(0.021)	(0.029)	(0.007)	(0.007)
MktBk	0.020***	0.021***	-0.017**	-0.017**	0.023***	0.028***	-0.013*	-0.012
	(0.006)	(0.006)	(0.008)	(0.008)	(0.006)	(0.008)	(0.008)	(0.008)
Profitability	0.092*	0.083*	0.175*	0.159*	0.072	0.058	0.158*	0.141
	(0.050)	(0.050)	(0.093)	(0.092)	(0.051)	(0.055)	(0.095)	(0.094)
DivPayer	-0.011	-0.012	0.060***	0.059***	-0.014	-0.024	0.054***	0.051***
	(0.013)	(0.012)	(0.013)	(0.013)	(0.012)	(0.016)	(0.013)	(0.013)
Tangibility	-0.045**	-0.044**	-0.099***	-0.102***	-0.052***	-0.049**	-0.091**	-0.090**
	(0.020)	(0.020)	(0.037)	(0.037)	(0.020)	(0.022)	(0.037)	(0.037)
CFvol	0.855***	0.837***	0.993**	0.999**	0.886***	0.790***	0.953**	0.932**
	(0.244)	(0.233)	(0.453)	(0.451)	(0.245)	(0.277)	(0.458)	(0.458)
RDexp	0.402***	0.404***	0.158	0.140	0.434***	0.406**	0.111	0.133
	(0.148)	(0.146)	(0.303)	(0.301)	(0.149)	(0.161)	(0.306)	(0.303)
Unrated	0.029***	0.030***	0.118**	0.118**	0.028***	0.030***	0.119**	0.118**
	(0.009)	(0.009)	(0.055)	(0.055)	(0.009)	(0.010)	(0.055)	(0.055)
BookLev	-0.343***	-0.350***	-0.211***	-0.210***	-0.349***	-0.359***	-0.214***	-0.218***
	(0.020)	(0.020)	(0.036)	(0.036)	(0.021)	(0.022)	(0.037)	(0.037)
Constant	1.228***	1.261***	0.801***	0.803***	1.245***	1.402***	0.814***	0.826***
	(0.160)	(0.139)	(0.118)	(0.118)	(0.147)	(0.199)	(0.119)	(0.120)
N	6832	6936	2182	2200	6820	6935	2175	2194
Model	IV Tobit	IV Tobit	IV Tobit	IV Tobit	IV Tobit	IV Tobit	IV Tobit	IV Tobit
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

the relatively few CDS firms that are not rated by S&P. *BookLev* (negative sign), *RDexp* (positive but not significant), and *Tangibility* (negative) are largely consistent with previous results, however, supporting the argument that the prospect of bankruptcy and the opaqueness of financials (which drives up monitoring and information-collection costs) increase debt concentration.

In summary, the CDS subsample results reported in Table 3 clearly demonstrate the effect that CDS trading has on debt structure, which is a significant increase in debt specialization. These results also enable us to build on Subrahmanyam et al. (2014) finding that CDSs cause a firm's default risk to rise. Our finding of a significant increase in debt specialization following the onset of CDS trading is consistent with the notion that it is being used as a mechanism for mitigating creditor conflicts and bankruptcy costs, the likelihood of which has increased following the onset of CDS trading.

4.1.1. Selection bias and CDS firms

Selection bias may be present in the sample of CDS firms. In particular, CDS firms are not chosen at random but are selected by derivatives trading desks. We use the Heckman two-step selection method to account for this bias and report the results in Table S.1 in the Internet Supplementary Material. The results show that, following the beginning of CDS trading, *HHI* increases, which is consistent with our previous results. The main variable of interest is statistically significant at the 5% level for columns (1)–(5) and at the 1% level for column (6). Although the magnitude and significance decline from the figures reported in Table 3, these results provide evidence that CDS trading leads to debt-structure concentration even after accounting for selection bias in the sample.

4.2. Bank lenders, lead arrangers, and debt concentration

So far, we have presented evidence indicating that the increase in bankruptcy risk that is a result of CDS trading is associated with debt specialization, which is consistent with the argument that these CDS firms concentrate debt structure to mitigate creditor conflicts and bankruptcy costs. An assumption inherent to this line of reasoning is that debt concentration equates with creditor concentration.[2] We find this assumption to be reasonable. In Table 4, however, we report the results of a direct test using bank-loan data obtained from the Dealscan database.

To conduct the analysis, we construct the following dependent variables (as defined in Appendix Table A.1): *HHI_Lenders, NumLenders, LeadArrShare, RepeatLender*, and *RepeatLeadArr*. For control variables, we include loan type (term loan, revolver, 364-day facility, and other) and loan purpose (corporate purposes, debt repayment, leveraged buyout/management buyout, takeover, working capital, commercial paper backup, acquisition line, and other), which are non-negative

[2] Kang et al. (2021) argue the opposite regarding repeat lead arrangers or lenders. Specifically, they argue that CDS trading makes it more likely that firms engage new or non-relationship lenders because CDSs (and observable credit spreads) reduce the adverse selection problem associated with lending. Their argument does not preclude debt specialization or lender concentration, as we posit here. Their analysis does not however consider borrowers' incentive structures. As we argue in this paper, borrowers may desire not only to reduce the number of lenders with which they engage but also to maintain existing relationships to avoid conflicts and reduce bankruptcy costs or to respond to financial distress.

count variables formed after collapsing (by summing) syndicated bank-loan data merged into the Dealscan dataset.[3]

Table 4 provides results for all five bank-loan dependent variables. In all regression specifications, the coefficient on *CDS_Active* is economically and statistically significant at the 1% level. Importantly, these estimates indicate that, after the onset of CDS trading, firms concentrate their debt structure. In short, *HHI_Lenders* increases, *NumLenders* decreases, *LeadArrShare* increases, *RepeatLender* increases (marginal effect of 6.54%), and *RepeatLeadArr* increases (with a marginal effect of 7.35%).[4] These findings indicate that firms concentrate debt structure, and therefore creditor structure, as a means of avoiding problems in bankruptcy. Taken together, the results reported in Tables 3 (using *HHI*) and Table 4 (using bank-loan data) suggest that, following the inception of CDS trading, firms concentrate not only debt structure but also debt ownership structure. It should be noted that this finding marks a contribution to the corporate finance literature on a topic that has not been fully explored.

4.3. PSM

Tables 3 and 4 provide evidence that, following the advent of CDS trading, firms concentrate debt structure as well as creditor structure. However, one might argue that this effect is driven by firm-level characteristics and not by CDSs. The literature attempts to address this argument by including the variable *CDS_Firm* in regression models as a means of controlling for time-invariant unobservable differences between CDS firms and non-CDS firms. In essence, *CDS_Firm* acts as an additional fixed effect and, through inclusion, applies to omitted variables or unobserved heterogeneity that could explain why a particular firm has a CDS contract traded on its debt.

We next use PSM to control for differences between CDS firms and non-CDS firms. With PSM we are able to generate a counterfactual sample of CDS firms that never had CDSs traded on their debt. By matching on determinants of capital structure, we create matches that closely resemble the sample of CDS firms, except for the treatment effect of CDS trading. Theoretically, if an unobservable variable, such as a confounding firm-level characteristic that is not controlled for in regression models, were driving our results instead of the treatment effect of CDS trading, we would expect the latent variable also to affect the *HHI* of non-CDS matched firms; this would be the case because the treated and untreated matched observations should be similar based on propensity scores.

In Table 5, we provide results derived from the PSM estimation model and from regressions on the matched sample for the dependent variable, *HHI*. Our methodological approach is based on similar techniques used by Subrahmanyam et al. (2014) and Narayanan and Uzmanoglu (2018a).[5] Column (1) details the regression results of estimating propensity scores. We regress ln*Size, MktBk, Profitability, DivPayer, Tangibility, CFvol, RDexp, Unrated, BookLev*, and industry and year fixed effects on *CDS_Active* to predict the probability that CDS trading occurs. Column (2) displays marginal effects on firm-level characteristics from the regression associated with column (1). ln*Size, MktBk, Profitability, DivPayer, Tangibility*, and *Unrated* are statistically significant at the 1% level, while *RDexp* is significant at the 10% level. The results reported in columns (3) and (4) represent regressions on the matched sample (2350 observations corresponding to CDS firms and 2350 observations with replacement by non-CDS firms), which we obtain by matching firms based on the estimated propensity scores reported in column (1). The coefficient on *CDS_Active* is economically and statistically significant at the 1% level in both columns. These results indicate that, even after controlling for firm-level characteristics through PSM, firms specialize their debt structure following the inception of CDS trading.

4.4. IV methodology

To control for endogeneity between debt specialization and CDS trading, we use two IVs that are widely used throughout the CDS literature. The first is *Lender FX Hedging*, which is the average foreign exchange hedging by a firm's bank lenders scaled by total assets per bank (Saretto and Tookes, 2013; Subrahmanyam et al., 2014), and the second is *Lender Tier 1 Capital Ratio*, which is the average Tier 1 Capital Ratio of a firm's bank lenders in a given year (Subrahmanyam et al., 2014). [6] The intuition underlying *Lender FX Hedging* is that, as foreign exchange hedging by lenders increases, other types of hedging (including the use of credit derivatives) increase as well. The intuition underlying *Lender Tier 1 Capital Ratio* is that, as capital declines, CDS trading likely increases as lenders seek capital relief through hedging exposure (Shan et al., 2014). In Table 6 we report our results obtained by instrumenting *CDS_Active* using *Lender FX Hedging* and *Lender Tier 1 Capital Ratio*.

In Table 6, columns (1)–(4), we report the estimates derived from an IV Tobit model specification where we instrument *CDS_Active* with *Lender FX Hedging*. We test for the IV relevance condition (i.e., whether the instrument is relevant to explaining variations in the variable of interest) by examining our first-stage results. In particular, the coefficient on *Lender FX Hedging* is statistically significant at the 1% level. We also perform Wald tests and fail to reject the null of no endogeneity. These results are available upon request. To demonstrate robustness, we provide three- and five-year averages for the full sample and the CDS subsample. *CDS_Active_Instrumented* yields economically and statistically significant coefficients in each of columns (1)–(4) in Table 6.

For columns (5)–(8), we instrument *CDS_Active* with *Lender Tier 1 Capital Ratio* and obtain results similar to those obtained with the previous instrument. We also test for the IV relevance condition and our unreported results are statistically significant at the 1% level. Like the results for the *Lender FX Hedging* instrument, those for *CDS_Active_Instrumented* are economically and statistically significant coefficients that we report in columns (5)–(8) of Table 6, and Wald tests fail to reject the null of no endogeneity. Both IVs corresponding to Table 6 provide evidence that firms concentrate or specialize their debt structures in response to the inception of CDS trading, even after accounting for endogeneity with an IV framework. To obtain additional unreported results, we also use the Big Bang Protocol as an IV, which conforms to the International Swaps and Derivatives Association's standardization of CDS contracts in 2009 (see Danis, 2017). The results are similar to those obtained using the other two IVs.

[3] Please note that the majority of CDS contracts trade on corporate bonds, not bank debt. Although they are illiquid, "loan only" CDSs (LCDS) do exist (Choudhry, 2011), albeit at lower relative trading volume. Also, it is probably safe to assume that a default on one debt instrument is positively correlated with default on others, especially given cross-acceleration and cross-default clauses.

[4] Amiram et al. (2017) document similar results regarding an increase in lead arranger share following CDS initiation. Our study goes considerably further than theirs, though, by examining other aspects of loan ownership structure, including lender concentration, the number of lenders, and repeat lenders and lead arrangers. Amiram et al. (2017) argue that the increase in lead arranger share as well as a corresponding increase in loan spreads result from information asymmetry between the lead arranger and other loan syndicate lenders after a CDS contract begins trading on a reference firm's debt.

[5] Although regression on a matched sample is used in the literature, Abadie and Imbens (2016) argue that the associated standard errors are biased because the regression does not account for the initial matching estimation stage.

[6] We use the table provided by the New York Federal Reserve Bank to link bank RSSDs to CRSP PERMCOs: https://www.newyorkfed.org/research/banking_research/datasets.html.

4.5. Additional robustness tests

For robustness purposes, we run logistic regressions on our second measure of debt specialization, *Excl90*, which is a dummy variable that equals 1 if any debt type represents 90% or greater of total debt and 0 otherwise and report the results in Table S.2. *Excl80, Excl70*, and *Excl60* are defined similarly. The results for the main variable of interest, *CDS_Active*, are stronger with this measure of debt concentration than the results previously obtained with *HHI*. In fact, the coefficient on *CDS_Active* is economically and statistically significant in all specifications, with an average marginal effect ranging from 14.1% in column (4) to 24.2% in column (1). As in Table 3, the controls are generally significant, with correct signs.

4.5.1. Ratings and CDS debt specialization

In this subsection we examine the extent to which our results are impacted by firms' bond ratings. Accordingly, we first create subsamples of our data divided into firms that are rated and firms that are not rated and then, for the rated group, further separate them into investment-grade and below-investment-grade ratings. We test for the impact of the inception of CDS trading on debt structure by regressing *CDS_Active* and controls for capital structure determinants on *HHI*. Of the 14,127 firm-year observations in the sample, 8094 observations (8066 for non-CDS firms and only 28 for CDS firms) correspond to unrated firms and 6033 observations (3505 for non-CDS firms and 2528 for CDS firms) correspond to rated firms. The vast majority of CDS firms are rated by S&P. They also tend to be larger on average (with total real assets of $15.61 billion for CDS firms and total real assets of $1.56 billion for non-CDS firms) and rated higher (BBB vs. BB).

Intuitively, we expect rated firms to have more debt financing options than firms that are unrated. This is the case because a firm that is not rated likely does not have access to public corporate bond markets and therefore has fewer debt types from which to choose. Because rated firms may have more debt options than those that are unrated, we expect to observe less specialization (i.e., higher diversification) in debt structure given the greater supply of capital. For Table S.3, we attempt to delineate the effect of CDS trading on rated firms and their debt structures by creating subsamples of rated, investment-grade-rated, and below-investment-grade-rated firms. All three sets of regressions include CDS and non-CDS firms.

In Table S.3, columns (1) and (2) we report statistically and economically significant results, providing further support for the argument that CDSs are associated with higher debt specialization. The main variable of interest, *CDS_Active*, is both economically and statistically significant, with a coefficient of 12.5% in column (2). Additionally, the control variable results are consistent with previous estimates. Our proxy variables for bankruptcy costs, *Tangibility* and *CFvol*, have significant negative and positive coefficients, respectively, and the proxy for opaqueness and monitoring costs, *RDexp*, has a significant and positive coefficient, as expected. We drop the variable *Unrated* for obvious reasons. The *CDS_Active* estimate is similar to the result reported in Table 3, which runs counter to intuition but is consistent with the argument that CDSs make bankruptcy more likely and therefore heightens the need for firms to mitigate this risk by increasing debt specialization, even for rated firms with more robust capital supplies.

Next, we run Tobit regressions for debt concentration on investment-grade-rated and below-investment-grade-rated firms. As in the previous discussion, here we attempt to further test the effect that CDS trading has on debt structure by examining targeted subsamples. However, in doing so we face the problem of smaller and smaller sample size, which results in estimates that are not statistically significant. In Table S.3, columns (3) and (4), the results reported show that the onset of CDS trading on investment-grade-rated firms has a significant impact of 7.77% in the full model, although many of the controls are not significant. Again, this result runs counter to intuition, where we would expect highly rated (low-credit-risk) firms that are unlikely to declare bankruptcy and hold more robust capital supplies to diversify their debt structures.

In Table S.3, columns (5) and (6), we report the results of a test of how CDS trading impacts the debt structure of below-investment-grade firms. We expect CDSs to exacerbate the bankruptcy risk in firms that are already at high risk because of their S&P credit ratings. Consistent with expectations, the coefficient on *CDS_Active* reported in column (6) is highly significant at a value of 10.66%. Additionally, the proxy variables for bankruptcy costs are both economically and statistically significant. The results reported in Table S.3, column (6) offer additional evidence that the inception of CDS trading affects debt structure through increased specialization of debt types—an effect made more pronounced by the below-investment-grade ratings given to these firms. The results reported in columns (1)–(4) indicate, however, that this effect is present in all rated firms, even including those rated as investment grade. In summary, the results contained in this section illustrate how CDS trading impacts debt structure irrespective of the method of dividing the dataset into subsamples.

4.6. CDS trading and debt composition

In the preceding section we provide evidence indicating that debt concentration also leads to lender concentration, at least with regard to bank loans. These findings are consistent with what we expect given the dynamics of the lender–debtor relationship in the presence of empty creditors. In this section, we analyze the impact of CDS trading on debt structure by separating public and private debt.

In Table S.4, we demonstrate that CDSs impact public debt (e.g., corporate bonds and notes) and private debt (e.g., a revolving credit line via a bank lender) differently, although the extent of the effect is linked to a firm's credit rating. Our data is separated into subsamples of firms that are rated as investment grade and below investment grade by S&P. We run OLS regressions using *CDS_Active* and control variables with two dependent variables: *BankDebt*, which is private debt consisting of term bank loans and drawn credit as a percentage of total debt; and *PublicDebt*, which consists of senior bonds and notes, subordinated bonds and notes, and commercial paper, all as a percentage of total debt. Results reported in columns (3) and (4) indicate the presence of a substitution effect following the onset of CDS trading between bank debt and public debt for firms rated below investment grade. Columns (5) and (6) display the full sample results and evince the same relationship, although it is less pronounced. Interestingly, however, for the investment-grade subsample associated with columns (1) and (2), the regression coefficients on *CDS_Active* are not statistically significant.

Closer inspection of these results suggests that they could reflect the effects of financial constraints as captured by S&P credit ratings. For investment-grade-rated firms that have readier access to capital markets and thus are less subject to financial constraints, we observe no statistical evidence of a substitution effect of private for public debt. In contrast, firms with poor creditworthiness (e.g., below investment grade) appear to switch out of bank debt in favor of public debt following the inception of CDS trading. In other words, the presence of a CDS market for firm-level debt may alleviate financial constraints that would otherwise block access to capital markets and, as such, access to corporate bonds and notes. This intuition is consistent with Saretto and Tookes (2013), who argue that CDS trading makes it easier for reference firms to increase both leverage and the maturity of debt. It is also consistent with Schwert (2019), who demonstrates that bank loans demand premium pricing despite seniority in bankruptcy over public debt, and Chava et al. (2019), who provide evidence indicating that rating downgrades of CDS firms are more impactful for firms that are situated near the investment-grade/below-investment-grade demarcation.

The analysis associated with Table S.4 examines a potentially competing story given the relative dispersion of public debtholders compared with bank lenders. This does not appear to be the case, however, for our sample of CDS firms. Among the CDS firms in our dataset, nearly all are rated by S&P, and approximately 70% of the corresponding firm-year observations are associated with an investment-grade rating. As indicated in Table S.4, we find no statistical evidence that investment-grade-rated firms substitute bank debt (low lender dispersion) for public debt (high lender dispersion). Furthermore, given their seniority in bankruptcy, we argue that bank-loan debt specialization, and the resulting bank-lender concentration that we show evidence for in Table 4, is most important. Seniority in bankruptcy coupled with empty crediting increases incentives for bank lenders to forgo out-of-court debt restructuring (see, e.g., Narayanan and Uzmanoglu (2018b), who examine prebankruptcy distressed exchanges). In response, we expect to see firms engage in debt specialization to mitigate this risk.

5. Conclusion

This paper investigates how CDSs impact debt structure by examining the before-and-after effect of CDS trading on a firm's specialization or diversification of debt types. We argue that CDS firms practice higher debt concentration than non-CDS firms to minimize creditor conflicts and bankruptcy costs. Our results indicate that firms engage more fully in debt specialization and are more likely to specialize after the inception of CDS trading. Additionally, we extend the analysis to include bank-loan data and find that, following the onset of CDS trading, the number of bank lenders drops while lender concentration increases, lead arranger share increases, and it is more likely that repeat lead arrangers and repeat lenders are involved. Finally, we implement PSM to control for differences in firm-level characteristics between CDS firms and non-CDS firms and IVs to control for endogeneity between debt concentration and CDS trading. In summary, following the onset of CDS trading, firms concentrate their debt structures as well as creditor structures, which is a novel finding and contribution to the literature.

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Brian Clark: Conceptualization, Methodology, Software, Formal analysis, Writing – review & editing. **James Donato:** Conceptualization, Methodology, Software, Formal analysis, Writing – original draft, Writing – review & editing. **Bill B. Francis:** Conceptualization, Methodology, Writing – review & editing.

Data availability

The authors do not have permission to share data.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jfi.2023.101029.

Appendix

Table A.1

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