Credit Default Swaps and Credit Risk Reallocation*

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Abstract

We use data on granular holdings of debt and Credit Default Swaps (CDS) referencing non-financial corporations across financial investors to investigate how CDS reallocate credit risk and whether this increases investor-level riskiness. To guide our investigation, we propose a methodology to disentangle CDS positions between three strategies: hedging, speculation, and arbitrage. In our dataset, arbitrage remains anecdotal. We find that CDS reduce exposure concentration, as hedgers shed off their most concentrated exposures, while speculators substitute debt for CDS. CDS also facilitate risk-taking by speculators. Overall, CDS increase portfolio risk metrics, due to a limited effect of hedging strategies compared to speculative ones.

Keywords: credit default swaps, credit risk.

JEL: E44, G11, G20, G23

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1 Introduction

CDS are controversial financial instruments - "weapons of mass destruction" according to W. Buffet. On the one hand, CDS might improve the allocation of credit risk allowing illiquid but optimistic investors to gain credit risk exposure according to Oehmke and Zawadowski (2015). They also enhance information efficiency as explained by Acharya and Johnson (2007). On the other hand, CDS reduce monitoring incentives because of the empty creditor problem modeled by Bolton and Oehmke (2011), and may even facilitate agents' coordination to "bad" equilibria as in Bruneau et al. (2014). These contributions primarily focus on how CDS affect asset prices or reference risk. However, they remain silent on distributional consequences for investor-level risk for at least two reasons.

First, CDS are a zero-sum game in aggregate and payoffs are merely transfers inside the financial system. However, recent contributions as Gabaix (2011) or Galaasen et al. (2020) stress how individual shocks may affect aggregate outcomes and credit supply in particular. As such, individual credit risk exposures matter for financial stability.[1] Second, studying individual credit risk requires granular data on multiple instruments (loans, bonds, CDS), which are difficult to access and process and have only recently been a focus of researchers.

Using granular quarterly data on both debt and CDS exposures by French investors on non-financial corporations (NFC) and Euro-Area (EA) banks on French NFCs from 2016$Q1$ to 2019$Q4$, we provide new answers to how CDS reallocate investors exposure to credit risk. Essentially, we show that CDS increase investors riskiness as measured by portfolio risk, with a stronger effect for dealers and investment funds than for banks.

To guide our empirical investigation, we build a methodology to disentangle and characterize investor strategies by reference and period. There are broadly three motives

[1] Studying credit risk at the individual level also finds support in bank capital regulation, which constrains the use of CDS for hedging purposes to debt instruments on the same reference. Article 213 of CRR (credit risk), "Subject to Article 214(1), credit protection deriving from a guarantee or credit derivative shall qualify as eligible unfunded credit protection where all the following conditions are met: (a) the credit protection is direct [...]".

behind CDS trading: arbitrage, hedging, and speculation. Arbitrageurs take offsetting positions in CDS and debt to benefit from relative price discrepancies. This strategy is anecdotal and represents 2% of CDS purchasers, and 0.02% of CDS sellers. Hedgers use CDS as an insurance product to downsize corresponding debt exposures, either in reaction to shocks, or to maintain lending relationships. Hedging represents from 13 to 19% of CDS purchase, and almost exclusively corresponds to shock hedging. Other types of offsetting CDS purchases add to 8%. Finally, speculators use CDS as an alternative venue to amplify debt exposures or to gain exposure without holding the underlying debt. The distribution of strategies already implies that the effect of CDS on individual portfolio risk mainly depends on speculative strategies pursued.

CDS are likely to affect individual investors portfolio risk for two reasons. They change investors' nominal exposures to references, allowing them to diversify or concentrate on the set of references they are exposed to. They also tilt the risk profile of investors reference base, and change the weights of positions with different contributions to portfolio variance. We analyze the effect of trading strategies on these two dimensions, and conclude on investors' portfolio risk.

First, CDS decrease exposure concentration, with hedgers purchasing CDS to cover their largest exposures, and speculators selling CDS when they hold relatively little underlying debt. In a model of risk-sharing with fixed costs, Atkeson et al. (2015) indeed predict that hedgers offset their largest debt exposures, but are unable to do so for small exposures in value. In addition, we also show that hedging ratios decrease for growing exposure concentration, controlling for size, which points to the existence of convex costs of hedging. The literature indeed shows that the relative liquidity of CDS over debt is higher for smaller trades (Biswas et al. (2015)). Since hedgers only represent a small fraction of CDS purchases, their impact on aggregate portfolio risk still remains moderate.

The most obvious use of CDS by speculators is to gain short credit risk exposures. Short-selling debt may involve costly frictions to which buying CDS is not subject.[2]

[2]Short-selling debt requires locating securities lenders and managing the risk of not finding securities sellers upon termination (Duffie et al. (2002); Nashikkar et al. (2011)).

Indeed, we find that 95% of short credit risk exposures trade through CDS. As regards using CDS as a substitute for debt, theory yields conflicting predictions. According to Che and Sethi (2014), speculators take advantage of CDS lower margin requirements to leverage their beliefs and double up their existing debt exposures. In contrast, CDS have lower trading costs than debt in Oehmke and Zawadowski (2015) and investors optimally choose their preferred instrument depending on their liquidity-belief profile. Therefore, CDS positions increase with debt in Che and Sethi (2014), while they decrease with debt in Oehmke and Zawadowski (2015). Our results corroborate Oehmke and Zawadowski (2015) view: investors sell more CDS if the reference debt accounts for a smaller proportion of their debt portfolio, both at the extensive and the intensive margin. However, Che and Sethi (2014) view prevails at the country or sector level of aggregation. This could stem from the sunk search costs of opening lending relationships (Boualam (2018)). Overall, CDS decrease investors exposure concentration across investor sectors, as measured by the Herfindahl-Hirschman Index (HHI) and the Gini coefficient. Short and long speculative strategies contribute to this decline, while hedging does not potentially due to decreasing hedging ratios at the intensive margin. CDS-induced diversification may also have a limited effect on return diversification since country and sector concentration increase.

Second, we ask whether CDS tilt investors relative risk exposures. We find that the use of CDS for short speculation increases with reference risk for banks and investment funds. Similarly, they shed off their riskiest exposures for hedging, which should be beneficial for their portfolio risk. The relative insensitivity of dealers to reference risk is consistent with their intermediation role in transactions, responding to demand rather than driving it. However, banks and dealers incentives to sell CDS increase with reference risk, a pattern that we do not observe for funds. These results hold controlling for bond and CDS relative liquidity. One explanation for dealers is that the higher demand for hedging and short-selling on riskier references reflects in higher risks borne by CDS selling counterparties. Since the margin advantage of debt increases with reference risk, our results imply that banks have higher incentives to benefit from it than funds, potentially due to the tighter capital-based regulations they are subject to.

Overall, accounting for CDS may have an ambiguous effect on portfolio risk. Investors might use CDS to diversify their exposures, but also to gain exposures to riskier references. In the last section, we show that CDS translate into higher portfolio risk for all sectors, the increase being stronger for dealers and investment funds. The rise in portfolio risk is driven by speculative strategies, both on the long and short sides. Hedging strategies mitigate it but represent a small share of strategies.

This paper contributes to three strands of the literature. First, we test theories from the literature on the determinants of risk management in general (Atkeson et al. (2015), Rampini and Viswanathan (2010)) and CDS trading in particular (Oehmke and Zawadowski (2015), Che and Sethi (2014)). In this empirical literature, among others, Bai and Collin-Dufresne (2019) analyze the determinants of the CDS-bond basis, and Oehmke and Zawadowski (2017) study how CDS traders value their relative liquidity. Our paper is closest to recent contributions using granular data such as Jiang et al. (2021) who explore US mutual funds liquidity and risk-taking motives, Gündüz et al. (2017) who show that higher standardization of CDS fosters higher hedging by German banks, Czech (2021) who studies spillovers between the CDS and bond markets, or Boyarchenko et al. (2018) who investigate the determinants of trading in the CDS or in the bond markets.

Our paper also speaks to the literature on CDS and risk-taking. A large literature has analyzed the effects of CDS introduction on debt markets. Ashcraft and Santos (2009) show that being referenced in CDS contracts results in small spread declines for safe firms, but the opposite for riskier firms. CDS also allow firms to increase leverage (Hirtle, 2009), and extend maturities (Saretto and Tookes, 2013). Subrahmanyam et al. (2014) shows that this translates in an increase in borrower risk, while Danis and Gamba (2018) emphasize how CDS reduce the likelihood of out-of-court restructuring for distressed firms. However, evidence on the impact of CDS on investor-level risk remains scant.

To the best of our knowledge, our paper is finally the first to examine how single-name CDS affect individual portfolio risk. In this respect, it lies at the crossroads of papers on how different asset classes contribute to portfolio risk (Hippert et al.

(2019) for CDS indices and Bessler and Wolff (2015) for commodities), and on how derivatives affect risk allocation (Hoffmann et al. (2018) for interest rate swaps).

The rest of the paper is divided as follows. Section 2 presents the data we collect. Section 3 discusses the methodology built to disentangle investors' strategies by reference. Section 4 presents and discusses the effect of strategies on concentration, risk-taking, and portfolio risk. Section 5 concludes.

2 Data

2.1 Credit default swaps

Investors can choose between two categories of instruments to gain credit risk exposure to a reference: debt or credit default swaps (CDS). Unlike debt, the reference entity is not a party to the CDS contract. CDS are derivatives where a buyer pays a premium, the CDS spread, to a seller to insure a notional amount of reference debt until the maturity date of the contract. If the reference defaults before maturity, then the seller pays the buyer the notional times the recovery rate resulting from an auction on the defaulted bonds. Therefore, CDS are both insurance contracts designed to hedge credit risk, and synthetic debt instruments because the payoff of selling a CDS is akin to the one of buying a bond on margin.[3] Because CDS are in zero net supply, they reallocate credit risk exposures between buyers and sellers.

2.2 Data collection

Banque de France grants access to granular supervisory data on financial institutions. We collect quarterly data from 2016Q1 to 2019Q4 on investors' credit risk holdings. The dataset includes three types of exposures: debt securities, loans, and CDS. Two

[3] Duffie (1999) or White (2014) provide detailed information on the valuation and pricing of CDS.

national registers, *OPC titres* and *Solvency 2*, report holdings at the ISIN level of respectively French investment funds and French insurers. The *Securities Holding Statistics-Group (SHS-G)* registry instead provides granular holdings of securities by EA banks. The scope of *SHS-G* data collection significantly increased in 2018Q3. Therefore, we remove derivative positions for these new banks prior to that date. Loans from French registered banks to NFCs are drawn from the French credit register. Finally, we use CDS data provided by the *Depository Trust & Clearing Corporation (DTCC)* to Banque de France under EMIR regulation. *DTCC* virtually includes all CDS contracts entered by a European Union (EU) counterparty. Banque de France access covers all French investors positions and EU investors positions on French references.[4] We uniquely identify investors and reference entities (issuers of securities and loans, and entities referencing CDS contracts) leveraging an enriched version of Eurosystem identification databases.[5] This identification database allows us to map the various entity or securities identifiers to a unique code. We come back to our consolidation strategy in Section 2.3. We then aggregate quarterly exposures from investors to references by instrument type.

We restrict our sample to investors trading at least one CDS over the period, and to NFCs referencing CDS at least once. We drop exposures to financial and sovereign references for which we do not have access to loan data. This allows us to focus on credit risk trading motives rather than counterparty risk.[6] Similarly, we exclude index CDS to restrict the set of plausible CDS trading strategies.[7] While index CDS are nowadays the most prevalent CDS category,[8] they represent smaller positions in our sample. As of 2019Q4, we observe €31bn of net positions in indices, to be compared with €54bn in single-name CDS.

[4]Appendix A provides more details on the cleaning procedure for EMIR data.
[5]The *Register of Institutions and Affiliates Database (RIAD)* provides information on legal entities while the *Central Securities DataBase (CSDB)* references information on individual securities relevant for ESCB statistics. We enrich them with several complementary data sources: *GLEIF* for the Legal Entity Identifier (LEI), national registers on parent relationships between NFCs, and manually identify the largest remaining ISIN.
[6]See Gündüz (2018) for empirical evidence on counterparty risk mitigation using CDS.
[7]Index CDS can be used for instance for macro-hedging purposes.
[8]As of 2019Q2, single-name CDS would represent $\sim$ \$0.5tn of net notional positions worldwide, while indices would stand at $\sim$ \$1tn (see ISDA (2019)).

Our dataset thus presents a near-exhaustive view of credit risk borne by investors on NFCs for two perimeters: French investors on all NFCs, and EA banks on French NFCs. National registers provide an exhaustive view for the first one, while we restrict EA banks' exposure to French NFCs because Banque de France EMIR access to non-French investors is limited to French references. We neglect non-EA subsidiaries of French banks bond exposures, non-French subsidiaries of French banks loan exposures, as well as EA banks cross-border lending to French NFCs, which is negligible in front of debt securities.[9] Thus, risk management at the French banking group level may occur in relation to unobserved debt holdings. When appropriate, we restrict our analyses to our fully exhaustive perimeter of French to French exposures.

We enrich our exposure database with investor and reference-level attributes. Reference ratings are collected from *CSDB* and from *Solvency 2*. We identify references in default using data published by *Creditex Group*.[10] We take time series of CDS spreads, CDS-bond basis,[11] and bond and CDS bid-ask spreads from *Eikon*. We also collect quarterly public CDS liquidity data on the top 1000 most traded references from *DTCC*.[12] Finally, we add references balance sheet and P&L data from the French register of firms *FIBEN*, *Eikon*, and *Orbis*. Table VII in the Appendix summarizes the key attributes of references by rating.

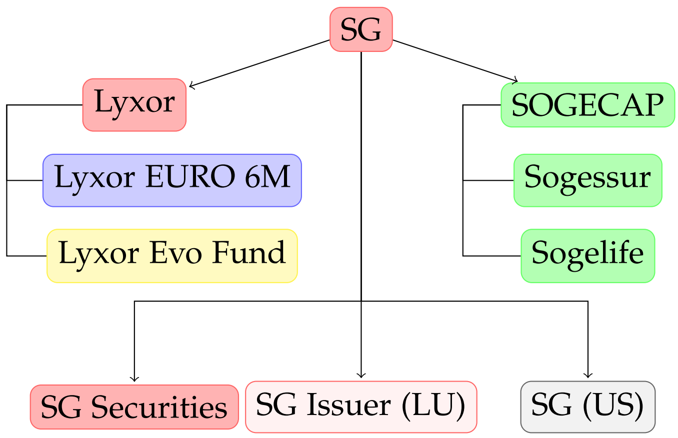
2.3 Our approach to consolidation

Banks and insurers are consolidated according to prudential perimeters. Indeed, CDS trading is generally undertaken at the group level, to manage risks arising from lending and investment activities at the legal entity level. Doing so, we remove intragroup holdings. We do not consolidate investors beyond prudential perimeters and thus do not observe risk management strategies for bank-insurance conglomerates. Indeed, banks and insurers are subject to different legal frameworks and consequently

[9] As of end-2019, cross-border lending represents 7% of loans to French NFCs in national accounts.
[10] https://www.creditfixings.com/CreditEventAuctions/fixings.jsp.
[11] The CDS bond basis defines as the difference between the CDS and the asset swap spread at a corresponding maturity.
[12] https://www.dtcc.com/repository-otc-data.

to separate reportings and risk management strategies even if they belong to the same conglomerate. Investment funds are left unconsolidated since risks are borne by fund shareowners. Fund asset managers are exposed to funds performance through fees and commissions, but with limited liability.

Figure I presents a stylised consolidation of Société Générale. Banking subsidiaries are consolidated at the ultimate parent level, including any non-insurance fully owned subsidiary (the asset manager Lyxor). Insurers are consolidated at the insurance group level. Investment funds are left unconsolidated. The stylised conglomerate splits into 4 different investors: the bank Société Générale and its observed subsidiaries, the insurer SOGECAP, and two investment funds, Lyxor EURO 6M and Lyxor Evo Fund.



Notes: One color corresponds to one investor in our sample. Bank affiliated entities for which we have all credit risk exposures are filled in red. We miss loan exposures from EA subsidiaries in light red, and we do not have any information from non-EA subsidiaries in grey. Insurers affiliated entities are in green. Funds are kept unconsolidated.

FIGURE I. Stylised consolidation for Société Générale

References are consolidated at their highest level of consolidation since CDS generally reference the ultimate parent while debt is issued at all levels of the group. This approach gives an exact view on credit risk exposure if default risk fully correlates within a reference group. However, limited liability clauses within a group may still distort our observation of real exposures.

2.4 Sample overview by investor

Table VI presents the number of investors and references in the pooled sample, and their size averaged across periods. By convention and throughout the paper, long exposures on credit risk (hold debt, sell CDS) are positive figures, while short exposures (short-sell debt, buy CDS) are negative.

Our sample includes 214 French investment funds, 41 EA banks (of which 3 French and 1 non-French dealers), and 3 French insurers. We split dealers from banks if the head of the banking group is included in the G16 list of derivative dealers.[13] French dealers account for the lion's share of CDS positions. They sell (buy) on average €25bn (14) single-name CDS, compared to €3bn (2) for funds, €3bn (4) for banks, and €1bn (0.06) for insurers. Banks and dealers lend on average €108bn to NFCs. Total average bond exposures stand at €118bn, of which insurers hold almost half. Because lending is essentially a domestic activity, investors lend essentially to French references (€104bn). However, they hold more bonds on non-French references - €87bn against €31bn. CDS trade on respectively 70 and 904 French and non-French NFC references. We observe a total of 35,621 investor-reference pairs over our sample. Figure VII in the Appendix presents net exposures to credit risk for French and non-French references by instrument type (loans, bonds, CDS) and sector as of 2019Q4.

Although single-name CDS represent a small fraction of aggregate credit risk exposures, their contribution to exposures to large firms whose idiosyncratic shocks may matter for aggregate outcomes is important. For instance, CDS selling represents over 20% of total credit risk exposures to CDS-referenced firms for 21% of funds and 37% of non-funds (see Figure VIII).

[13]The group of the sixteen largest derivatives dealers (G16) includes Bank of America, Barclays, BNP Paribas, Citigroup, Crédit Agricole, Credit Suisse, Deutsche Bank, Goldman Sachs, HSBC, JP Morgan Chase, Morgan Stanley, Nomura, Royal Bank of Scotland, Société Générale, UBS, and Wells Fargo.

3 A methodology to disentangle strategies

3.1 Description of the methodology

CDS trading motives can be broadly grouped into three categories, as Oehmke and Zawadowski (2017), or Boyarchenko et al. (2018) emphasize. Investors can use CDS for hedging to downsize their credit risk exposure. This strategy covers two cases. First, investors may want to adjust their exposure in response to a shock. This motive underpins risk management modeling approaches as in Atkeson et al. (2015) or Rampini and Viswanathan (2010). Second, a bank may be willing to maintain a valuable lending relationship and extend a loan while not being able to bear the associated risks. This motive corresponds to the textbook case of J.P. Morgan's first CDS purchase on Exxon during the 1989 oil spill.

Investors also exchange CDS for speculation purposes, in particular since CDS buyers are not required to hold the underlying debt. In that respect, CDS are an alternative trading venue for credit risk investment. Non-redundancy with debt has been the focus of several contributions. Oehmke and Zawadowski (2015) highlight the liquidity advantage of CDS, arguing that they are a more standardized product, with smaller inventory costs, and price-impact of trading. Che and Sethi (2014) or Garleanu and Pedersen (2011) contend that leverage constraints are looser for selling CDS than for purchasing bonds on margin. Jiang et al. (2021) discuss the opacity advantage of CDS attributable to their smaller market value (null at inception) and their off-balance sheet reporting.

A last trading motive arises from the coexistence of debt and CDS. Borrowing at the risk-free rate and purchasing debt should have the same payoff as selling a CDS referencing that debt with the same maturity. In practice, market imperfections give rise to the CDS-bond basis, the spread difference between the two strategies. Bai and Collin-Dufresne (2019) extensively discuss this arbitrage opportunity.

Our methodology aims at disentangling these three trading strategies by exploiting the sign, ratio, and timing of matched debt and CDS positions at the investor-reference-quarter level. A trading strategy for CDS_{ijt} is defined as the reason why an investor i holds a CDS on reference j at quarter t.

Investors who do not hold CDS on a reference are *standard* investors. Among investors trading CDS, we first examine whether debt and CDS exposures (weakly) amplify or (strictly) offset each other. Investors are *speculators* when CDS and debt amplify each other. Speculators may be *naked* if investors hold no underlying debt on the reference.

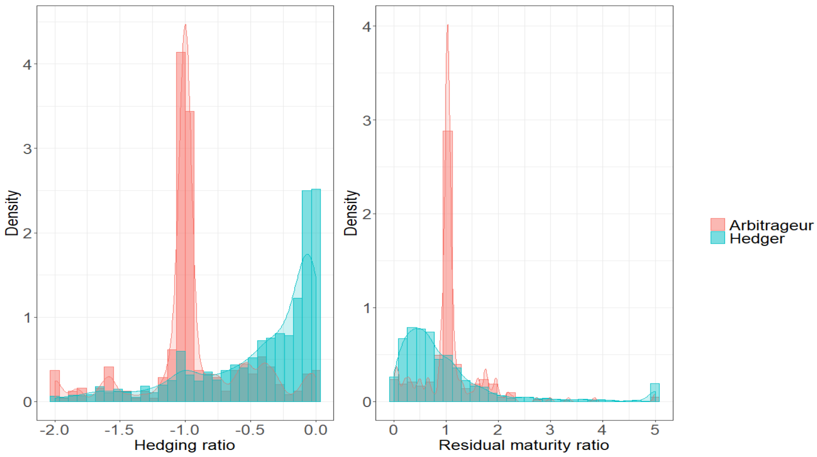
Investors with offsetting debt and CDS exposures are named *offsetters*. Among them, we first single out positions whose hedging ratio, the ratio of the CDS notional over the underlying debt exposure $\frac{CDS_{ijt}}{Debt_{ijt}}$, is below -2. These investors are *naked speculators* since most of the CDS creates a negative net position rather than offsets existing debt. Among remaining positions, we split *hedgers* from *arbitrageurs* using the aforementioned definition of hedging. Hedgers are investors entering a CDS position when already holding the underlying debt (hedging occurs in response to a shock), or acquiring simultaneously both positions if at least part of the debt is a loan (hedging occurs to maintain a lending relationship). Conversely, arbitrageurs simultaneously acquire offsetting CDS and bonds.

Finally, when entry is not observed because the CDS exposure is already observed at 2016Q1, we exploit exit patterns and relative hedging ratios for identification. The latter is required since investors hedging bonds in response to shocks may be indistinct from arbitrageurs if they exit simultaneously in bond and CDS. We posit that hedgers exit either first in CDS, or simultaneously in debt and CDS with part of the debt being a loan, or simultaneously in debt and CDS with a hedging ratio more likely to be that of a hedger. Arbitrageurs on the other side exit simultaneously in bond and CDS and exhibit a hedging ratio more likely to be that of an arbitrageur. In practice, we find that all but one hedging exposure are related to maintaining a lending relationship.

Our strategy leaves us with a number of *other* strategies which correspond to positions for which entry and exit are unobserved, or follow uninterpretable patterns. More details on the methodology can be found in Appendix C.1.

3.2 Hedgers vs Arbitrageurs

Disentangling hedgers from arbitrageurs crucially relies on the timing of entries and exits. To assess whether this approach allows separating strategies of a different nature, we examine the distribution of two important statistics. Figure II represents the pooled distribution of each strategy's hedging ratio (on the left-hand side), and residual maturity ratio.[14] As expected, the hedging ratio distribution of arbitrageurs exhibits a clear mode around -1 (resp. 1 for the residual maturity ratio). This reflects the vanilla arbitrage strategy, which consists of buying a bond on margin and covering its face value with a CDS of identical notional. In contrast, the median hedging ratio of hedgers stands at 26%, while the mean residual maturity ratio is around 0.5 years (see Table VIII).



Notes: Distributions before the identification of offsetters already existing as of 2016Q1 (step 4 of the methodology described in Appendix C.1). By convention, purchasing a CDS gives rise to a negative CDS position hence the negative hedging ratio. Residual maturity $RESMAT$ is the average maturity for the investor-reference holdings weighted by debt holdings or CDS positions.

FIGURE II. Pooled distribution of hedging ratios $\frac{CDS_{ijt}}{Debt_{ijt}}$ (lhs) and residual maturity ratios $\frac{RESMATCDS_{ijt}}{RESMATDebt_{ijt}}$ (rhs) for hedgers and arbitrageurs purchasing CDS

Another distinctive feature of the difference between CDS purchased by hedgers and arbitrageurs is the CDS-bond basis. As discussed in Bai and Collin-Dufresne (2019), the negative basis prices four risks.[15] Assuming arbitrageurs have a relative advan-

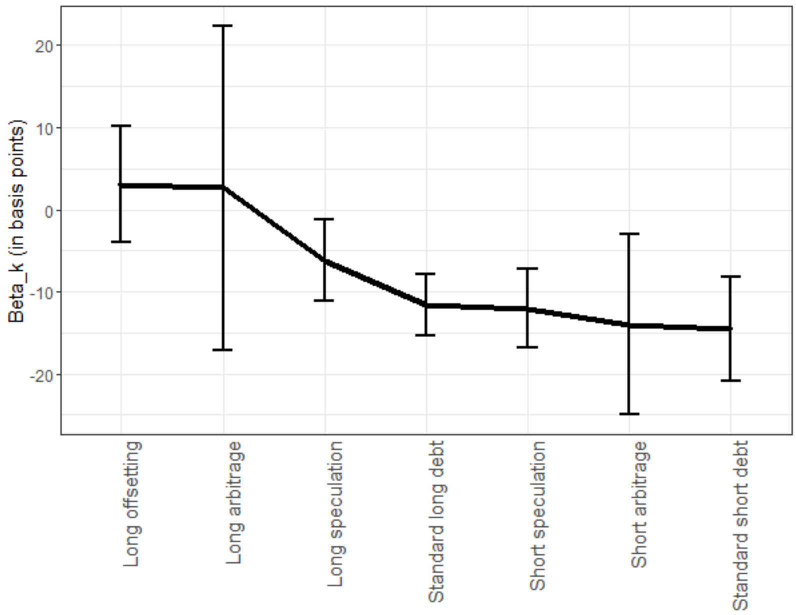
[14]Residual maturities are a notional-weighted average of residual maturities of all exposures consolidated at the investor-reference-quarter level.

[15]Bond collateral value variation, bond liquidity risk, investor funding risk, and counterparty risk in

tage in managing those risks, the more negative the basis, the more profitable the arbitrage strategy. We formally test whether CDS subject to arbitrage strategies exhibit a different basis with Equation 1.

$$CDSBondBasis_{ijt} = \alpha Spread_{jt} + \sum_k \beta_k Strategy^k_{ijt} + FE_{it} + \epsilon_{ijt}, \tag{1}$$

with $Spread_{jt}$ the reference CDS spread to control for credit risk, and FE_{it} investor-quarter fixed effects. Figure III plots the coefficients associated with each strategy, and Table IX in Appendix D provides the econometric estimates and shows that these results also hold controlling for bond and CDS liquidity. Arbitrage strategies combining a CDS and a bond purchase (*short arbitrage*) involve CDS with a basis 14 bps lower than for other offsetting strategies involving the purchase of a CDS (*short offsetting*). Taken together, these analyses make us confident hedgers and arbitrageurs have different trading motives.



Notes: Bars represent 90% confidence interval. Standard errors are clustered at the investor-quarter level. By convention, short strategies involve buying CDS, and long strategies selling CDS. Speculators include naked speculators. CDS-bond basis are winsorized at the 1% level. The pooled data contains 9 long arbitrage and 481 short arbitrage positions.

FIGURE III. Mean CDS-bond basis by strategy vs *Short offsetters excl. short arbitrageurs*

the CDS market.

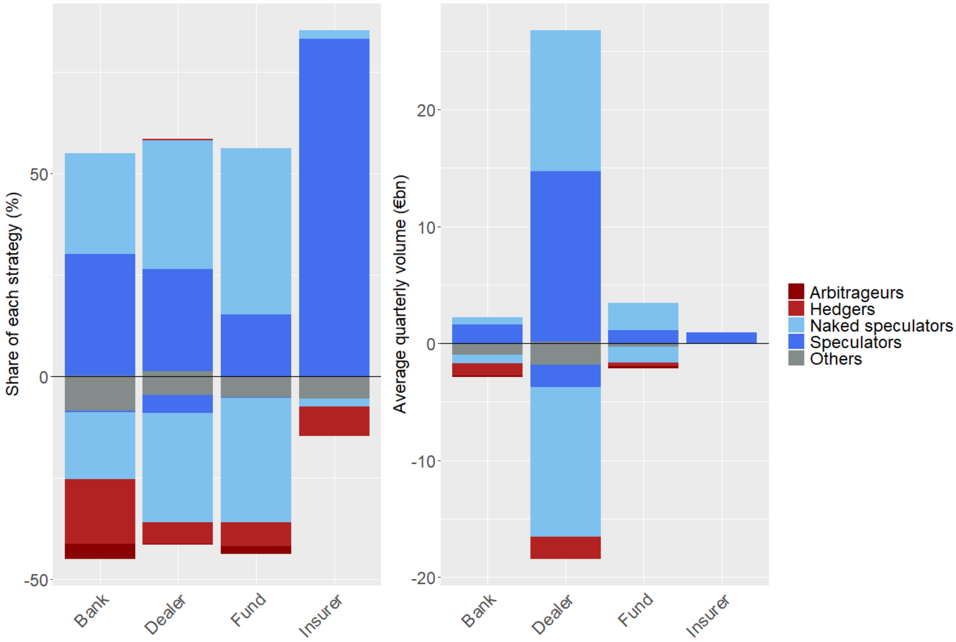
3.3 Trading strategies in the sample

Figure IV plots the shares and notional amounts of strategies by investment sector.[16] Overall, dealers represent the bulk of exposures with 79% of notional CDS exchanged (resp. 60% of CDS positions in number). Investment funds represent 10% of the notional (resp. 23% of positions) with the largest share of naked speculators, while banks account for 9% of the notional (resp. 15% of positions) and the largest share of hedgers. Arbitrage is a minor activity essentially undertaken by investment funds and banks. Insurers' participation in the CDS market is anecdotal. Figure IX in Appendix C.2 presents the evolution of those strategies over time with signed CDS positions.

Descriptive statistics by strategy can be found in Table VIII in the Appendix. They point to other differences between strategies. For instance, arbitrageurs exhibit a similar turnover for debt and CDS positions, while hedgers exhibit the highest CDS turnover - consistent with the idea that they use them to adjust credit risk exposures in response to shocks. Strategies involving CDS trading are about twice less persistent than standard debt positions.

Our analysis highlight that a small percentage of CDS purchased offset preexisting debt exposures: between 74% for banks, 36% for funds, and 20% for dealers. Among these offsetting purchases, an even smaller share can be classified as hedging: 35% for banks, 13% for funds, and down to 10% for dealers. As shown in Figure IX, these figures are relatively stable over time and the variation in net positions is essentially driven by speculation.

[16] Our results are in line with Jiang et al. (2021) contribution who find that 59% of investment funds are long speculators, 17% are short naked speculators, and 23% of them are offsetters. In our pooled dataset, 24% of funds are short speculators including naked speculators (28% of all entities), 62% are long speculators including naked (resp. 58%), and 14% are offsetters (resp. 14%).



Notes: Strategy shares correspond to the share of each strategy in absolute notional CDS exposure by investor sector, with negative values corresponding to short CDS positions.

FIGURE IV. Pooled share (lhs) and average volume (rhs) of strategies by sector

4 Results

4.1 CDS decrease credit risk concentration

In this section, we study the effect of CDS on credit risk concentration. Speculators use CDS as a substitute for debt while hedgers offset their largest exposures. This translates in a decrease in credit risk concentration, as measured by the Herfindahl-Hirschmann Index (HHI) or the Gini coefficient, both at the investor and reference level.

According to Atkeson et al. (2015), risk-sharing motives increase participants' incentives to hedge their largest exposures, while the fixed cost of hedging prevents them to do so for small exposures in value.[17] Two alternate views emerge from the literature on speculators. According to Che and Sethi (2014), speculators sell CDS to take synthetic leverage on references on which they are optimistic, taking advantage of relatively low margin requirements. CDS are thus a complement to debt. In contrast,

[17]This fixed cost of hedging originates in the legal expenses paid to create a trading desk and to connect to market infrastructures needed for contract payments.

Oehmke and Zawadowski (2015) argue that speculators sell CDS instead of holding debt to benefit from higher liquidity in the CDS market. CDS and debt are then substitutes. We test these predictions on the likelihood of adopting these strategies, as specified in Equation (2):

$$Y_{ijt} = \Lambda \left(\beta \frac{Debt_{ijt}}{TotExp_{it}} + X_{ijt} + FE_{it} + FE_{jt} \right) + \epsilon_{ijt}, \tag{2}$$

where Y_{ijt} is a dummy for CDS trading strategies like speculating or hedging, FE_{it} are investor-quarter and FE_{jt} reference-quarter fixed effects. The independent variable of interest is $\frac{Debt_{ijt}}{TotExp_{it}}$. It measures the share of investor i exposure to reference j in quarter t, as a percentage of total debt exposures. X_{ijt} designates the log of either the debt exposure, either the total credit risk exposure. For speculating strategies, if CDS are a complement (resp. a substitute) for debt, then β is positive (resp. negative). If predictions from Atkeson et al. (2015) hold, then β should be positive for hedging strategies.

Here and in following econometric estimations, our identification crucially relies on reference-quarter and investor-quarter fixed effects. In the spirit of Khwaja and Mian (2008), we use reference-quarter fixed effects to abstract from any changes in reference characteristics. Since one reference may belong to multiple investor portfolios, the propensity to trade CDS then depends uniquely on the relative concentration of that reference in investors portfolios. Symmetrically, we use investor-quarter fixed effects to control for entity-level risk demand and focus simply on how relative risk concentration determines the demand for CDS.

Table I presents the baseline results. Results from the first column support the predictions from Atkeson et al. (2015). Hedgers offset their exposures representing a larger share of their portfolio and with larger values. On average, the odds ratio of hedging increases by 106% when the share of debt exposure increases by 1pp, while that of speculation decreases by 62% conditionally on speculators being long on debt. This result is obtained on a sample of strictly positive debt positions. Hedgers incentives stand in contrast with those of other CDS purchasers, for which the effect of debt concentration is opposite in column (2). Non-hedging offsetters typically buy fewer CDS on their more concentrated exposures. For instance, arbitrage is typically a relatively small strategy as highlighted in Table VIII.

However, the opposite goes at the intensive margin. Conditional on purchasing CDS, Table X in the Appendix shows that hedging ratios are larger for more concentrated exposures. Although we control for exposure size, this could pertain to convex costs of hedging since CDS liquidity is higher for small transactions as Biswas et al. (2015) highlight.

Columns (3) and (4) from Table I show that the probability to sell CDS on a reference is lower when the share of debt in investors portfolio is high. This result holds both conditionally on holding the reference's debt (column (3)) or conditional on being weakly long in both debt and CDS (column (4)). This result confirms predictions from Oehmke and Zawadowski (2015). Speculators use CDS as an alternative trading venue for debt. The results appear even stronger in column (4) which accounts for naked speculative strategies. This is also consistent with the idea that investors have fixed risk budgets per reference, that they subsequently jointly decide to allocate in debt and CDS markets. Results also hold at the intensive margin as Table X exhibits. Not only do investors speculate less on concentrated debt exposures, but when they do so, they tend to sell relatively fewer CDS. We also find decreasing CDS shares as the size of the exposure grows, in line with the lower liquidity of CDS for higher trades.

Our results on hedging are consistent with Gündüz et al. (2017) who find that German banks increased hedging on larger and riskier exposures after the CDS "Small Bang". Our analysis corroborates these results for a larger set of financial institutions and emphasizes how debt concentration is an important driver of hedging. However, we also find that concentration is a motive for hedging up to a certain point. Investors hedging ratio is smaller in magnitude for the largest exposures. Regarding speculation, we add to Acharya et al. (2018) who showed how German banks less exposed to peripheral European sovereign CDS increased CDS selling most throughout the European sovereign crisis. We show in particular how investors sell CDS to complete their exposure to specific market segments.

We run the same estimations with exposures aggregated at the country or sector level

	P(Hedger)	P(Other Short Offsetter)	P(Speculator)	
	(1)	(2)	(3)	(4)
Share debt exposure	31.43^{***}	-27.83^{**}	-12.47^{**}	-139.07^{***}
	(8.54)	(11.78)	(5.59)	(14.51)
Log Debt	0.46^{***}	0.42^{***}	-0.02	
	(0.03)	(0.04)	(0.01)	
Log Total				-0.07
				(0.07)
Num. obs.	14794	12471	37322	50165
Inv x Quarter FE	Y	Y	Y	Y
Ref x Quarter FE	Y	Y	Y	Y
Cluster SE	Inv x Q	Inv x Q	Inv x Q	Inv x Q
IBP correction	Y	Y	Y	Y

Notes: Estimation of Equation (2) on a subsample of long debt investors. "Share debt exposure" designates $\frac{Debt_{ijt}}{TotExp_{it}}$. "Log Debt" corresponds to $Log(Debt_{ijt})$, and "Log Total" to $Log(Debt_{ijt} + CDS_{ijt})$. Columns (1) to (3) are restricted to a sample of strictly positive debt exposures. Column (4) is restricted to a sample of strictly positive total credit risk exposures and weakly positive debt and CDS exposures. Coefficients are corrected from the incidental parameter bias using the methodology developed by Fernández-Val and Weidner (2016). $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

TABLE I. Probability to enter strategies and concentration of debt exposure

using the NACE-21 sectoral classification. Results are housed in Appendix Table XI. Likewise, investors purchase CDS on their more concentrated exposures to protect from country sectoral-level shocks to which they are disproportionately exposed. In contrast with results on speculators, investors are more likely to sell CDS referencing a specific country/sector if their portfolio share is high. Instead of using CDS as a substitute for debt, it seems that investors use CDS to leverage up their beliefs or information on specific markets, taking advantage of preferred information they earn from their original debt exposures. While Oehmke and Zawadowski (2015) prediction holds at the investor reference level, investors are more likely to behave in the sense of Che and Sethi (2014) prediction at the country or sector-wide level. One explanation could be the fixed cost of lending relationships: investors then focus on their most profitable relationships and sell CDS on the remaining references of their area of specialization.

We now seek to understand how different strategies affect portfolio exposure concentration. In the following, we compare concentration indices computed over debt exposures (with a subscript "Debt") only or over debt and CDS exposures (with a subscript "Debt + CDS"). Two complementary measures are used to quantify credit risk concentration: the HHI and the Gini coefficient.[18] Larger indices indicate higher levels of credit risk concentration. Investor-reference exposures take two values, depending on whether CDS are included:

$$Exp_{ijt} = \begin{cases} Debt_{ijt}, & \text{for debt only} \\ Debt_{ijt} + CDS_{ijt}, & \text{for debt and CDS} \end{cases}.$$

Investor i HHI at quarter t writes:

$$HHI_{it} = \sum_{j} \left(\frac{|Exp_{ijt}|}{\sum_k |Exp_{ikt}|} \right)^2.$$

Likewise, investor i Gini coefficient at quarter t writes:

$$Gini_{it} = \frac{\sum_{k,l} \big| |Exp_{ikt}| - |Exp_{ilt}| \big|}{2n_{it} \sum_k |Exp_{ikt}|},$$

with n_{it} the number of references investor i is exposed to. Symmetrically, we compute both indices at the reference level. We test whether accounting for CDS affects HHI and the Gini coefficient by estimating Equations (3) for investors and (4) for references (with analog equations for Gini coefficients):

$$\frac{HHI_{Debt+CDS,it} - HHI_{Debt,it}}{HHI_{Debt,it}} = \text{SECTOR}_i + \epsilon_{it}, \tag{3}$$

and:

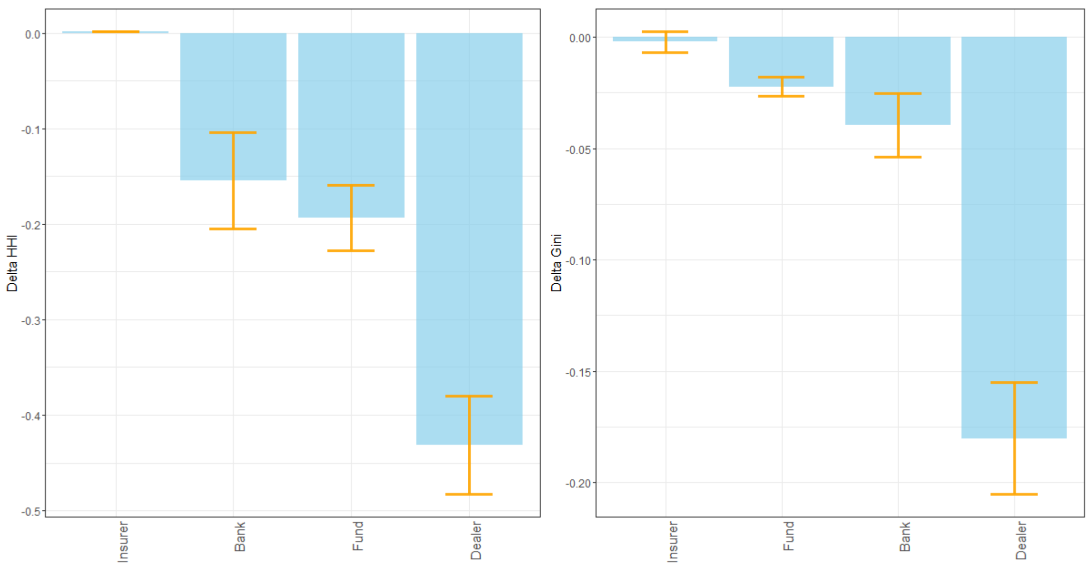
$$\frac{HHI_{Debt+CDS,jt} - HHI_{Debt,jt}}{HHI_{Debt,jt}} = I(FR)_j + \epsilon_{jt}, \tag{4}$$

[18]The HHI and Gini coefficients have different statistical properties. For example, null exposures do not change the HHI whereas they decrease the Gini coefficient. We include all null exposures to CDS-referenced firms in our Gini measure to account for the diversification benefits of naked CDS speculation.

with investor sector $SECTOR_i$, and $I(FR)_j$ a dummy for French references. We add the latter since we observe a smaller share of exposures for non-French exposures (we do not observe their loan-borrowing outside France, for instance).

Table II presents the results (plotted in Figure V) and confirms that CDS decrease the concentration of credit risk among investors. This finding is valid with both HHI and Gini coefficients. The effect of CDS on portfolio concentration is the largest for dealers, with a 43% (HHI) and 18% (Gini) drop in concentration indices. CDS also decrease the concentration of banks and funds portfolios but the magnitude of the effect is smaller with 15% (resp. 19%) for banks (resp. funds) HHI. Likewise, CDS on average increase the set of investors exposed to a reference. They decrease references HHI by 4% for French exposures, while non-French exposure concentration remains unchanged (the Gini coefficient of French references decreases though).

HHI　　　　Gini coefficient



Notes: Bars represent 95% confidence intervals. Estimates are those presented in Table II.

FIGURE V. Variation of concentration indices by sector

Both investors and reference credit risk concentration might be endogenous to CDS trading and referencing. For instance, investors may choose to hold lower debt exposures knowing that they can complement their exposure through selling a CDS. We address this concern in the discussion Section 4.4. To do so, we increase the sample and compare investors trading (resp. references) CDS to those not trading (resp. referencing) CDS with two different identifications. Results in Tables XIV and XV do not

	Δ HHI Inv (1)	Δ HHI Ref (2)	Δ Gini Inv (3)	Δ Gini Ref (4)
Bank	-0.15^{***}		-0.04^{***}	
	(0.05)		(0.01)	
Dealer	-0.43^{***}		-0.18^{***}	
	(0.05)		(0.02)	
Fund	-0.19^{***}		-0.02^{***}	
	(0.03)		(0.00)	
Insurer	0.00^{***}		-0.00	
	(0.00)		(0.00)	
Non FR Ref		-0.01		-0.02^{***}
		(0.03)		(0.00)
FR Ref		-0.04^{***}		-0.01^{***}
		(0.01)		(0.00)
Num. obs.	742	2151	24101	2151
Cluster SE	Inv	Inv	Inv	Inv
Adj. R^2	0.10	-0.00	0.05	0.01

Notes: Estimation of Equation (3) (columns (1) and (3)) and (4) (columns (2) and (4)). Dependent variables are expressed in percentage change versus the index calculated excluding CDS. Concentration indices are winsorized at the 5% level. Entity-quarters with at least 5 CDS positions have been kept. Reference-level variables have the suffix "Ref", and investor-level with the suffix "Inv". $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

TABLE II. Investor-level effect of CDS on credit risk concentration: changes in HHI and Gini coefficient

point to a significant correlation between CDS trading or referencing and investors or references debt concentration.

We also leverage our methodology to relate investors strategies with the concentration of credit risk. We discriminate between long and short speculators (including naked ones), short hedgers, and other strategies involving CDS trading. Table XII in the Appendix presents the results. All speculative strategies translate into lower exposure concentrations, both between and within investors. This result is consistent with speculators using CDS as a substitute for debt. Perhaps surprisingly, hedging does not reduce exposure concentration except in one specification. This could be expected since hedging declines with exposure size at the intensive margin.

4.2 CDS and risk-taking

In this section, we explore the relationship between CDS trading strategies and reference risk. We show that banks and investment funds resort more to short speculation and hedging on riskier references while this is not the case for dealers. We also find that banks and dealers long on credit risk use CDS to increase risk-taking, in contrast with funds.

We explore the correlation between CDS trading strategies and reference spreads. Taking for granted the nature of the final exposure, we seek to understand whether CDS strategies relate to reference spreads significantly different from standard long or short debt strategies. We estimate the following logistic equation:

$$\mathbb{P}(CDS \neq 0)_{ijt} = \Lambda\Big(\beta Sector_i \times Spread_{jt} + \gamma_1 log(|Total|)_{ijt} + \gamma_2 X_{jt} + FE_t + FE_i\Big) + \epsilon_{ijt}, \tag{5}$$

where $log(|Total|)_{ijt}$ designates the log of the absolute total (CDS plus debt) credit risk exposure and X_{jt} designates reference-level controls including bond and CDS measures of liquidity, reference gross debt, the CDS-bond basis, and a dummy taking value 1 if the reference is French.

The results are housed in Table III. Column (2) studies the probability to use CDS for short credit risk investors, the ones having a negative total (CDS and debt) exposure to credit risk. Using CDS on these strategies significantly relates to CDS spreads for banks and investment funds, but does not for dealers. If disagreement between investors increases as reference risk rises, we would indeed expect more CDS trading to occur on riskier references (Oehmke and Zawadowski, 2017). The odds of trading CDS are also increasing in the size of the short position. This latter finding confirms investors' preference for CDS instead of debt in implementing short credit risk positions. Column (3) instead discusses the case of short offsetters, investors being long on debt and weakly short on CDS. Hedgers make the bulk of these investors. We find that offsetters are more likely to purchase a CDS for higher spread references, the interaction between investors sectors and reference spreads is significant for banks and investment funds. Dealers are not sensitive to reference risk in both columns (2) and (3), potentially because their role is to intermediate transactions and adapt their inventories to client demand.

As regards long credit risk only investors in column (1), we find that higher spreads relate to a higher propensity to trade CDS for banks and dealers, but not for funds. We further dig into this result in the following paragraphs.

In these analyses, we control for the liquidity of bonds and CDS as measured by the bond and CDS bid-ask spreads, and adding a dummy if the reference is one of the top 1000 most traded CDS in that quarter. As expected, we find that higher CDS liquidity correlates with more CDS trading for all strategies. Short credit risk strategies also strongly relate to bond illiquidity, while this is not the case for other strategies. In the end, the higher demand for speculation or hedging on riskier references may explain why CDS bid-ask spreads decline as rating deteriorates (see Table VII).

Banks and dealers thus seem to use CDS to engage in risk-taking on long credit risk exposures, but not investment funds. We illustrate this by rating in Figure VI. The figure presents the unconditional share of CDS in long credit risk exposures by rating for banks and dealers pooled together, and for funds. Banks and dealers share of CDS in long credit risk exposures increases with lower rating, while the opposite goes for funds.

In Table IV, we study this question between ratings by estimating Equation (6), and successively adding controls.

$$\mathbb{P}(CDS \neq 0)_{ijt} = \Lambda\Big(\beta Rating_{jt} + \gamma_1 log(|Total|)_{ijt} + \gamma_2 X_{ijt}\Big) + \epsilon_{ijt}, \qquad (6)$$

where X_{ijt} first includes only a dummy for the reference being French and a control for gross debt (columns (1) and (4)), then includes liquidity and CDS-bond basis controls (columns (2) and (5)), and finally adds investor-quarter fixed effects (columns (3) and (6)).

Funds do not appear to statistically change CDS trading when rating changes, after controlling for investor and quarter fixed effects (column (6)). On average, funds trade

	$P(CDS \neq 0)$			
	Long Credit Risk Only	Short Credit Risk Only	Short offsetter	Long offsetter
	(1)	(2)	(3)	(4)
Bank:Spread	0.48^{***}	1.02^{***}	0.43^{***}	-4.06^{**}
	(0.08)	(0.37)	(0.09)	(1.63)
Dealer:Spread	0.37^{**}	-0.01	0.04	-0.62^{***}
	(0.15)	(0.14)	(0.06)	(0.23)
Fund:Spread	0.03	6.79^{***}	0.33^{***}	-73.02^{***}
	(0.04)	(1.95)	(0.07)	(11.17)
Log |Total|	0.09^{**}	0.09^{***}	-0.06^{**}	0.22^{***}
	(0.04)	(0.01)	(0.03)	(0.07)
FR Ref	-0.28^{***}	2.43^{*}	0.94^{***}	-2.33^{***}
	(0.07)	(1.44)	(0.12)	(0.62)
Log TA Ref	-0.27^{**}	-1.29	0.45^{**}	-0.78^{**}
	(0.11)	(1.11)	(0.21)	(0.37)
CDS bid-ask spread Ref	-5.53^{***}	-4.60^{***}	-6.52^{***}	-10.51^{***}
	(0.36)	(0.56)	(0.74)	(2.48)
Bond bid-ask spread Ref	-0.13	2.81^{***}	-0.70^{*}	3.86
	(0.17)	(0.52)	(0.37)	(6.32)
Top1000 CDS liquidity Ref	0.94^{***}	1.15^{***}	1.75^{***}	0.15
	(0.10)	(0.26)	(0.24)	(0.41)
Log Gross debt Ref	0.00	-0.04	-0.01	-0.07
	(0.02)	(0.07)	(0.03)	(0.11)
Basis Ref	-0.00	-0.00	-0.00^{***}	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Num. obs.	27594	4678	13090	363
Investor FE	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y
Cluster SE	Inv x Q	Inv x Q	Inv x Q	Inv x Q

Notes: Estimation of Equation (5). Columns (1) and (2) include respectively only long (resp. short) credit risk strategies. Columns (3) and (4) include only strategies with long (resp. short) debt and weakly short (resp. long) CDS positions. Insurers are excluded from the analysis. Spreads are right-winsorized at 1%. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

TABLE III. Probability to trade CDS depending on sector and demand for credit risk

CDS on lower-rating references, but a given fund does not change its relative demand for CDS when reference risk changes.

Our results on investment funds stand in contrast to those of Jiang et al. (2021). In their paper, US mutual funds notional-weighted CDS sell spreads are significantly larger than their weighted bond spreads. We replicate their analysis on our universe of French investors and exposures. Column (1) of Table XIII in the Appendix confirms that only banks and dealers engage in risk-taking in our sample.

The fact that dealers increasingly sell CDS when ratings deteriorate might mirror their clients' demand. If clients prefer to hedge riskier references, then dealers appear to sell more CDS on riskier references. However, this would not explain why banks are more subject to risk-taking than dealers in Table III.

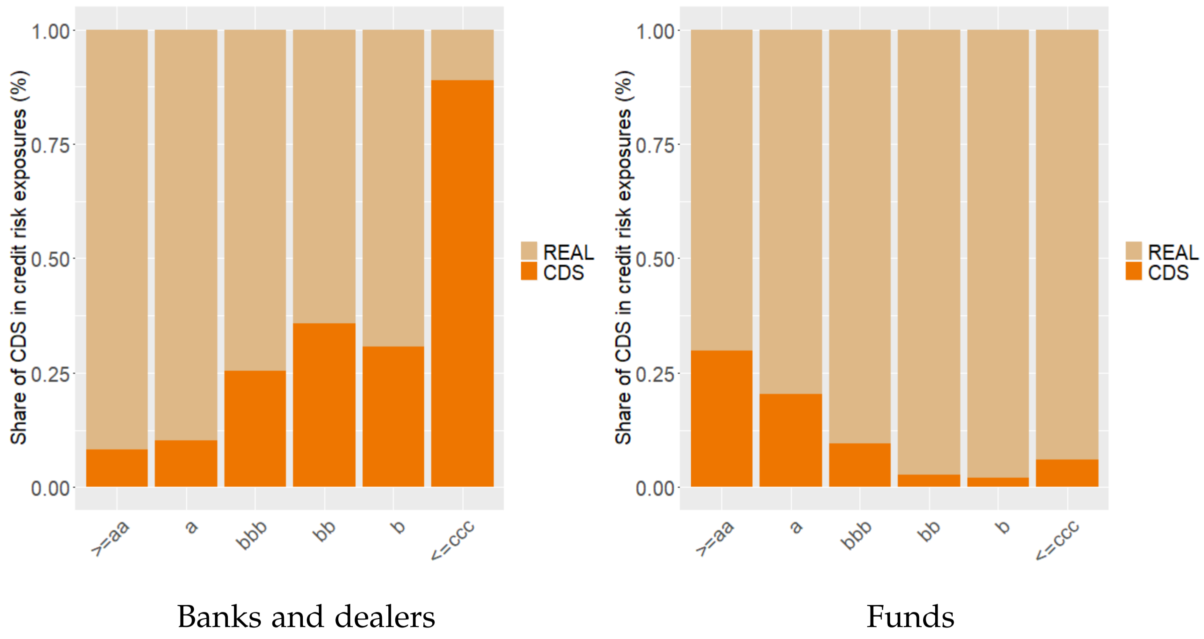


FIGURE VI. Pooled distribution of the share of CDS positions in investors long credit risk exposures by rating and sector

Several relative properties of bonds and CDS are correlated to reference risk. First, the liquidity advantage of CDS increases when ratings deteriorate. CDS relative liquidity may be higher for riskier references for which debt issues are more fragmented, and debt trades smaller.[19] As evidenced in Table VII, CDS bid-ask spreads indeed decline when ratings worsen, while exactly the opposite goes for bond bid-ask spreads. However, our correlation between trading CDS and risk-taking continues to hold controlling for relative liquidity, which suggests other channels are at play. The margin advantage of CDS also potentially increases for riskier references. As Darst and Refayet (2018) note from FINRA,[20] initial margins required to purchase an investment grade (100 bps spread) bond on margin are 10% of the purchase market value. This compares to 4% of the notional to sell a CDS with the same spread on a 5 years maturity. The difference rises when rating deteriorates: the initial margin required

[19] Oehmke and Zawadowski (2017) show that more CDS trading happens when the corresponding debt securities are more fragmented. Biswas et al. (2015) show that CDS are relatively more liquid for trades up to 500k$, while the opposite holds for larger trades.

[20] FINRA 4210 and 4240 rule-books on initial margins are available here https://www.finra.org/rules-guidance/rulebooks/finra-rules.

	$P(CDS > 0)$					
	(1)	(2)	(3)	(4)	(5)	(6)
a	0.79^{***}	0.40^{***}	0.29^{***}	0.03	-0.22^{**}	0.32^{*}
	(0.08)	(0.10)	(0.11)	(0.08)	(0.09)	(0.16)
bbb	1.17^{***}	0.77^{***}	0.62^{***}	-0.29^{***}	-0.72^{***}	0.07
	(0.08)	(0.11)	(0.12)	(0.09)	(0.09)	(0.15)
bb-b	1.04^{***}	1.01^{***}	0.75^{***}	-0.98^{***}	-1.03^{***}	0.24
	(0.11)	(0.16)	(0.21)	(0.13)	(0.17)	(0.22)
$\leq$ccc	1.37^{***}	-0.03	-0.82^{**}	0.35	-11.38^{***}	-6.72^{***}
	(0.18)	(0.48)	(0.36)	(0.28)	(0.27)	(0.74)
Log Total	0.07^{***}	-0.01	-0.01	0.56^{***}	0.63^{***}	1.37^{***}
	(0.03)	(0.02)	(0.02)	(0.05)	(0.05)	(0.07)
FR Ref	-1.86^{***}	-1.95^{***}	-3.48^{***}	-0.05	-0.43^{***}	-0.26^{***}
	(0.14)	(0.17)	(0.11)	(0.04)	(0.06)	(0.10)
CDS bid-ask spread Ref		-2.80^{***}	-3.69^{***}		-7.05^{***}	-6.48^{***}
		(0.61)	(0.66)		(0.71)	(0.84)
Bond bid-ask spread Ref		-0.17	-0.31		-0.40^{*}	-0.80^{***}
		(0.21)	(0.22)		(0.22)	(0.28)
Top1000 CDS liquidity Ref		0.65^{***}	0.96^{***}		-0.14	0.12
		(0.11)	(0.13)		(0.14)	(0.18)
Log Gross debt Ref	-0.08^{***}	-0.15^{***}	-0.17^{***}	-0.08^{***}	-0.10^{***}	-0.09^{***}
	(0.01)	(0.02)	(0.03)	(0.01)	(0.02)	(0.03)
Basis Ref		-0.00	-0.00		0.00^{*}	0.00
		(0.00)	(0.00)		(0.00)	(0.00)
Num. obs.	23108	7437	6553	90256	31727	9237
Sector	Banks	Banks	Banks	Funds	Funds	Funds
Inv x Quarter FE	N	N	Y	N	N	Y
Quarter FE	Y	Y	N	Y	Y	N
Cluster SE	Inv x Q	Inv x Q	Inv x Q	Inv x Q	Inv x Q	Inv x Q

Notes: Estimation of Equation (6). Regressions on a subsample of long credit risk speculators with respect to references rated $\geq$ aa. Banks include dealers. Reference-level variables have the suffix "Ref". "Log Total" refers to total (CDS and debt) credit risk exposures. "Top1000 CDS liquidity Ref" is a dummy taking value 1 if the reference is among the top 1000 most globally traded references in the period. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

TABLE IV. Probability to sell CDS by rating for long speculators by sector

to purchase a non-listed high-yield bond on margin amounts to 50% of its market value whereas it stands at 25% of the notional to sell a 700 bps spread with a 5 years maturity.

Our results imply that banks and dealers pay more attention than investment funds to the margin advantage of CDS with respect to bonds when they engage in long speculating strategies. This may be related to the tighter capital regulations they are subject to.

4.3 CDS increase investors portfolio risk

Our analyses suggest that accounting for CDS has an ambiguous effect on individual risk since CDS increase portfolio diversification, but are also used for risk-taking. In this section, we evaluate these offsetting effects and how they ultimately contribute to an increase in portfolio risk.

We examine how portfolio risk metrics change when accounting for CDS. Our approach builds on the literature measuring how different asset classes contribute to portfolio risk (see for instance Hippert et al. (2019) for CDS indices, or Bessler and Wolff (2015) for commodities). We focus on two standard risk metrics. First, we examine daily portfolio realized volatility, which is traded off with returns in Markowitz (1952) model with CARA utility. We also compute changes in realized returns. Then, we analyze 10-days Value-at-Risk (VaR), a standard measure of portfolio risk at least since Linsmeier and Pearson (2000). As discussed in Pritsker (2006) or Kuester et al. (2006), simply examining the historical distribution of returns ignores the non-iid nature of data, and is subject to jumps as the estimation window rolls. Therefore, we use the filtered historical simulation method introduced by Barone-Adesi et al. (1999). It consists of filtering out shocks from a $GARCH(1,1)$-specified history of returns and simulating 10-days ahead returns.[21]

Analyzing portfolio risk requires a definition of CDS returns and portfolio weights. We use the first-order approximation from Junge and Trolle (2015) to compute reference j daily CDS returns from the perspective of sellers as:

$$r_{j,t} \approx -(Spread_{j,t} - Spread_{j,t-1}) \left(T_{j,t} - \frac{1}{250} \right) + \frac{Spread_{j,t}}{250}, \tag{7}$$

with $Spread_{j,t}$ the par-spread of reference i on date t and $T_{j,t}$ its remaining time to maturity.[22] The first term corresponds to the change in the CDS par market value, which decreases sellers' return as maturity approaches. The second term refers to interests accruing to the seller. Additionally, we assume the CDS-bond basis is null,

[21]For each quarter, we initialize simulations using 30-day means immediately lagging quarter-ends.

[22]We assume CDS spreads are quoted on an average of 250 working days per year and that the risky duration approximately equals the time to maturity.

which allows us to use the same return for debt and CDS. We also take an average time to maturity T of 2.5 years - in line with the residual maturity on CDS positions in the sample. Portfolio weights are defined as the signed exposure divided by the sum of signed exposures. They write formally for investor i on reference j, $w_{ijt} = Exp_{ijt} / \sum_k Exp_{ikt}$, with Exp_{ijt} adding the debt and the CDS exposure. Therefore, we allow for negative weights when investors short sell bonds or buy CDS.

We compute mean return, volatility, and VaR at the investor quarter level using portfolio weights with and without CDS, and compute the percentage change in the metric when accounting for CDS. This writes for example as $\Delta Vol_{it} = (Vol_{Debt+CDS,it} - Vol_{Debt,it}) / Vol_{Debt,it}$ for the volatility metric.

Table V presents how CDS alter portfolio risk by investor sector (specifications (1) to (3)) and strategy (specification (4) to (6)). CDS significantly increase investors portfolio volatility and VaR. Dealers and funds VaR respectively increase by 43 and 50 % in absolute value, while returns increase by 12 and 9%. The rise in portfolio risk is smaller in the case of banks, who experience a VaR increase of 19% and no significant change in returns. This important increase reflects the high share of CDS in credit risk exposures to CDS-referenced firms.

Specifications (4) to (6) investigate how the intensity of different strategies at the investor-quarter level relates to portfolio risk. The rise in portfolio risk mostly stems from long and short speculating strategies. Although speculation diversifies exposures, it contributes to a rise in sectoral and country-level concentration as we have seen in Section 4.1. We have also shown in Section 4.2 that CDS enable some investors to increase risk-taking. Hedging mitigates this rise allowing for exposure diversification in particular on the riskiest references. However, it only accounts for a small share of strategies.

Still, results on investors' portfolio risk could be plagued by endogeneity if investors jointly choose their debt and CDS portfolio. For instance, investors could decide to reduce risk-taking in debt when they start to speculate with CDS. We test the relation between investors debt portfolio risk and CDS trading in Section 4.4, and do not find any correlation between both.

	Δ Return	Δ Vol	Δ VaR	Δ Return	Δ Vol	Δ VaR
	(1)	(2)	(3)	(4)	(5)	(6)
Bank	-7.323	18.994^{**}	18.644^{**}			
	(5.854)	(9.584)	(7.948)			
Dealer	11.875^{***}	47.595^{*}	43.375^{**}			
	(2.586)	(26.319)	(19.746)			
Fund	8.618^{*}	50.503^{***}	49.983^{***}			
	(4.618)	(14.163)	(14.003)			
Insurer	0.260^{***}	0.776^{***}	-4.426^{***}			
	(0.000)	(0.000)	(0.000)			
Intercept				-0.557	-2.723^{***}	-1.489
				(0.398)	(0.776)	(0.970)
ShortHedger				-128.199	-397.058^{***}	-355.756^{**}
				(91.751)	(100.098)	(141.636)
LongSpeculators				29.875^{***}	13.635	19.501^{*}
				(9.468)	(9.736)	(10.314)
ShortSpeculators				36.879	401.325^{***}	392.110^{***}
				(23.262)	(48.576)	(67.330)
OtherCDS				-76.931	379.031^{**}	313.581^{**}
				(81.632)	(153.121)	(146.828)
Num. Obs.	742	742	742	3,153	3,153	3,149
Adjusted R^2	0.020	0.012	0.010	0.063	0.445	0.344
Cluster SE	Inv	Inv	Inv	Inv	Inv	Inv

Notes: We winsorize risk and return metrics at the 1% level. Dependent variables are the difference in percentage points between portfolios with CDS and portfolios without CDS. We change the sign of differences in value-at-risk to give the same sign interpretation to volatility and value-at-risk changes: an increase in value-at-risk corresponds to an increase in portfolio risk. Returns are average daily realized returns over the past quarter. Volatility is calculated as $\sigma_{i,t} = \sqrt{^T W_{i,t} Var(S)_t W_{i,t}}$, with $W_{i,t}$ the weights of i portfolio, and $Var(S)_t$ the covariance matrix of daily returns on a 5-y rolling window. "Δ VaR" corresponds to the percentage change in 10-day value-at-risk using the filtered historical simulation method. Strategies are continuous variables equal to the absolute notional CDS value of each strategy by investor-quarter, divided by the sum of absolute CDS and absolute debt exposure of each investor-quarter. In column (1) to (3), we restrict our regression to investor-quarters holding at least 5 CDS. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

TABLE V. Effect of investors sectors and CDS trading strategies on portfolio risk

4.4 Discussion

Throughout the paper, we implicitly take investors debt exposures as given. This follows a theoretical (Atkeson et al., 2015) and empirical (Oehmke and Zawadowski, 2017; Jiang et al., 2021) tradition which rests on the assumption that debt is less liquid than CDS. This might not hold in general equilibrium since CDS trading on a reference is likely to affect both firms' decision to issue debt and investors' decision to hold debt.

Empirical contributions on the effect of CDS on reference firm debt tend to show that

CDS trading induces firms to issue more debt at lower rates (Hirtle, 2009; Saretto and Tookes, 2013; Gündüz et al., 2017), and ultimately become riskier (Subrahmanyam et al., 2014). Our conclusions on risk-taking by banks and dealers and portfolio risk are then conservative: not only do CDS cause higher reference risk, but traders will sell CDS on the riskiest entities, and end up with yet riskier portfolios. Similarly, if CDS inception increases reference outstanding debt, then its dispersion in the financial system will be higher if there are fixed costs of trading for instance.

CDS and debt holdings are also likely to be jointly determined by investors. This endogeneity of debt positions to the possibility to trade CDS may affect all our results. First, CDS could fallaciously appear to reduce exposure concentration. If investors anticipate they can gain credit risk exposures using CDS instead of debt, they may choose not to hold debt and sell CDS instead. Alternatively, lenders may choose to lend more to a given firm knowing they can hedge off part of the exposure going forward. If this hypothesis holds, CDS-referenced firms should *ceteris paribus* have a more concentrated set of lenders than the rest. Second, investors could choose to purchase less debt of CDS-traded references for which CDS have a relative advantage. If CDS are relatively attractive for lower ratings, investors may downsize debt to the benefit of CDS. This would bias our results on risk-taking and portfolio risk. The increase in portfolio risk would then only stem from the reduction in debt portfolio risk. We address these concerns in turn.

First, we test the relation between reference debt concentration and CDS referencing. To do so, we include in our sample the 3000 firms representing the largest debt holdings by quarter in our sample, and yet not referencing any CDS. Firm debt concentration is still measured as $HHI_{jt} = \sum_i \left(\frac{|REAL_{ijt}|}{\Sigma_k |REAL_{kjt}|} \right)^2$ for firm j at period t.

We run three different types of regressions. Specifications (1) presents a baseline OLS regression on the full sample of references. The OLS estimation is defined as:

$$HHI_{jt} = \gamma_1 \mathbf{1}_{CDSRef_j} + \gamma_2 Grossdebt_{jt} + FE_j + FE_t + \epsilon_{jt} \tag{8}$$

with $Grossdebt_{jt}$ the reference gross debt, $\mathbf{1}_{CDSRef_j}$ a dummy if CDS trade on the reference at time t, FE_j is a reference fixed-effect, and FE_t a time fixed-effect.

Specifications (2) and (3) consist in a staggered difference-in-difference estimation. The estimations are similar to equation (8) with time plus individual fixed effects but run on two sub-samples with different treatment and control groups. Specification (2) measures the effect of CDS referencing for firms that start referencing a CDS, with firms never referencing CDS as a control group. Specification (3) bears on the opposite case, firms that stop referencing CDS with firms always referencing CDS as a control group.

Finally, specifications (4) and (5) restrict to firms that start (4) or stop (5) referencing a CDS during the period and run an event study on them. The study lies ± 4 quarters around the introduction or termination of CDS referencing. To control for trends across time, we subtract to firms HHI the mean HHI over the two control groups. The specifications equation:

$$\overline{HHI}_{jt} = \gamma_1 \mathbf{1}_{CDSRef_j} + \gamma_2 log(Grossdebt_{jt}) + FE_j + \epsilon_{jt} \tag{9}$$

with $\overline{HHI}_{jt}$ the reference HHI minus the mean HHI over the control group at the same period.

The distribution of firms referencing CDS splits as follows. 347 firms always reference a CDS, while 2873 never reference any CDS. 63 firms start while 79 firms stop referencing CDS during the period. 240 firms both enter and exit CDS referencing. These latter are not included in the difference-in-difference estimations nor in the event study. The number of firms referencing at least once a CDS (729) is smaller than the total number of firms referencing in the data Section 2 since we restrict the analysis to firms with valid gross debt. Every specification includes firms' gross debt as a control. As expected, gross debt negatively relates to lenders' concentration. The results from Table XIV in the Appendix do not indicate a significant relationship between CDS referencing and lenders' concentration of debt exposures. Even if the identification from specifications (2) to (5) is loose in the sense that CDS referencing decision might be endogenous to investors' exposure concentration, the results allow us to address the endogeneity concern since the correlations are not significant.

Second, we test the relation between investors trading CDS and the concentration of their debt portfolios. In the same vein, Table XV in the Appendix presents specifications similar to those from Table XIV. In contrast, it applies to an extended panel of all investors holding debt in our database. The difference-in-difference estimations and event studies also run on investors that start or stop trading CDS during the period. The distribution of investors from the extended sample splits as follows. 41 investors always trade CDS, 2431 never trade CDS, 22 investors start while 22 of them stop trading CDS during the period. Finally, 49 investors start and stop trading CDS during the period. We drop these from the analysis on entry and exit from the CDS market. We add investors' total debt exposure as a control in the regressions. Likewise, the relationship between CDS trading and debt portfolio concentration is not significant. Investors do not seem to alter the concentration of their debt portfolios at the onset of CDS trading.

Third, we address the endogeneity concern on investors risk-taking. We test the relation between the mean debt portfolio spread and CDS trading for a sub-sample restricted to investors' standard or long speculating strategies. The set of specifications is similar to those in the tables above. Table XVI in the Appendix shows that investors' debt portfolio spread does not significantly relate to CDS trading, except for one specification for which the relation is positive.

Fourth, we test the relation between debt portfolios risk and CDS trading to focus on the endogeneity concern between investors' debt portfolio risk and CDS trading. The results are housed in Table XVII in the Appendix. Likewise, debt portfolio risk measured by the Value at Risk does not significantly relate to investors' CDS trading.

5 Conclusion

In this paper, we use quarterly granular data on both debt and CDS exposures to study how CDS reallocate credit risk. To guide our investigation, we propose a methodology to disentangle investor-reference pairs trading CDS into three strategies: speculators use CDS to amplify their original debt exposures; hedgers use them to reduce debt exposures after unexpected shocks or to maintain lending relationships; arbitrageurs make profit out of the CDS-bond basis.

Overall, CDS decrease exposure concentration, with some nuances. Speculators use them as a substitute for debt, but also to double up on country and sector level specialization. Hedgers offset in priority their largest debt exposures, albeit with decreasing hedging ratios at the intensive margin. Then, we show that CDS facilitate risk-taking. Banks and investment funds are more likely to buy CDS on riskier references to gain short credit risk exposures or to hedge debt exposures. Dealers and banks tend to sell relatively more CDS on riskier references, while funds don't. We take this as evidence that the former derive more benefits from the growing margin advantage of CDS with reference risk, potentially due to tighter capital regulations. For dealers, this may also mirror the higher demand for hedging and short speculation on riskier references. Finally, CDS increase investors portfolio risk, the effect being stronger for dealers and funds. The rise in portfolio risk is particularly driven by speculating strategies. Although hedging decreases portfolio risk, its share in CDS motives for trade is too small to balance the rise in portfolio risk caused by long and short speculation.

Overall, our results emphasize the importance of accounting for CDS when analyzing credit risk distribution. CDS facilitate risk-taking, and since they represent a large share of exposures to large firms, they make investor portfolios significantly riskier. As granular risk matters for aggregate outcomes and financial stability, our paper calls for adding CDS to granular risk measurements, and for properly incorporating CDS effects on individual risk in cost-benefit assessments. We leave this analysis of the impact of CDS on systemic risk through increased granular risk for future research.

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A Cleaning CDS positions from DTCC reports

EMIR (648/2012) regulation compels EU institutions to report their derivative transactions to trade repositories, which in turn transfer the relevant data perimeter to regulators. We use quarter-end credit derivatives reports to DTCC from 2016Q1 to 2019Q4. Abad et al. (2016) find that DTCC dataset accounts for the bulk of transactions that fall under EMIR scope. Since major dealers report their trades to DTCC, data from this trade repository is representative of the European market for credit derivatives. We apply a series of treatments to clean the data. First, we remove transactions for which the column CCP is filled but no counterparty is a CCP. These are old alpha transactions that are novated with a CCP and that the counterparties forgot to terminate. Second, we enrich the data with FX rates to convert notionals in euros and we match the contract ISIN with Anna-DSB to retrieve the ISIN (or index name) of the reference. Third, transactions are de-duplicated and turned into one-liner observations. We remove observations if the two reporting counterparties disagree on key fields: reference, contract type, notional, currency, contracts resulting from compression, execution date, maturity date, intragroup dummy. Fourth, we remove transactions with missing execution date, maturity date, reference, or valuation. We also drop intragroup transactions, position components, and transactions with notionals under (and above) €$1,000$ (€10bn). Finally, we restrict our dataset to credit default swaps contracts and remove more exotic contracts such as spread bets or swaptions.

B Descriptive statistics

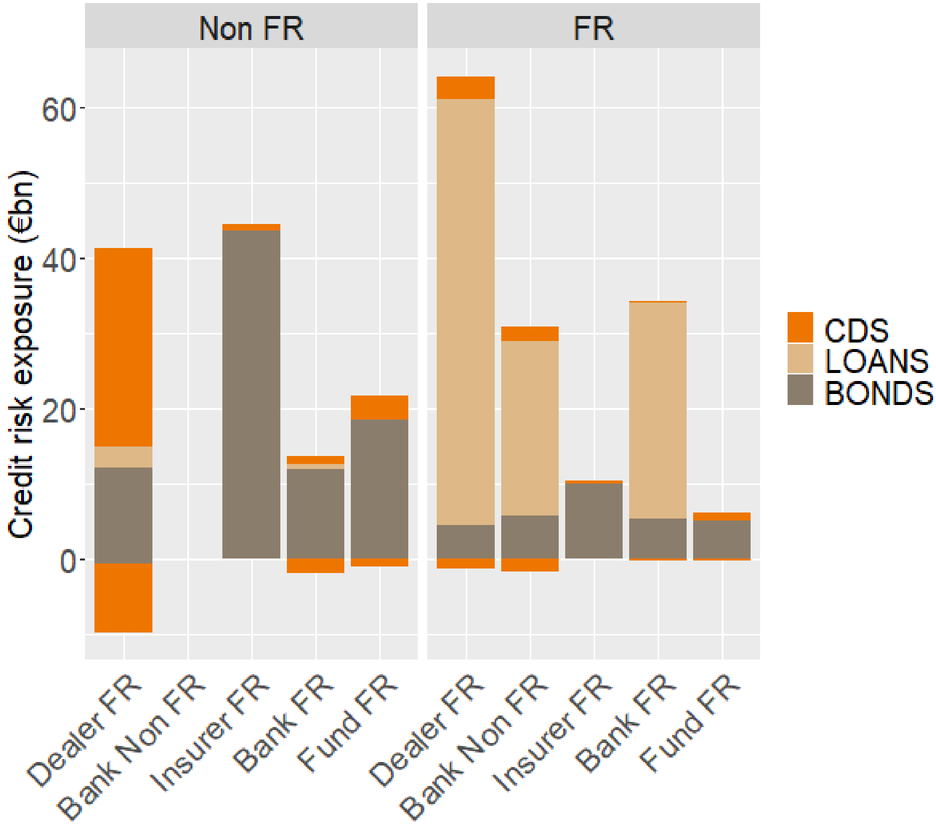

FIGURE VII. Debt and CDS exposures to NFC by investment sector and residence of reference as of Q4 2019

Category	#Obs	CDS sell	CDS buy	#CDS sell	#CDS buy	Bonds long	Bonds short	Loans
Bank FR	3	0.94	-1.94	121.33	142.50	17.68	-0.01	28.71
Bank Non FR	35	2.14	-1.60	157.17	76.17	5.62	-0.13	20.85
Dealer FR	3	24.68	-13.73	811.33	524.50	15.26	-0.94	58.14
Fund FR	214	3.30	-1.83	322.83	258.00	25.89	-0.00	0.00
Insurer FR	3	1.07	-0.06	57.00	8.50	53.94	0.00	0.00
NFC FR	70	6.22	-3.99	333.33	219.50	31.29	-0.28	104.20
NFC NFR	904	25.91	-15.17	1136.33	790.17	87.09	-0.80	3.50
All	35621	32.13	-19.16	1469.67	1009.67	118.38	-1.08	107.70
Bond	135	2.03	-1.31	241.00	190.17	19.83	0.00	0.00
Mixed	54	1.27	-0.50	81.67	57.83	5.08	-0.00	0.00
Other	25	0.00	-0.01	0.17	10.00	0.98	0.00	0.00

Notes: "#Obs" is the number of observations in the pooled post-2018Q2 sample. "#CDS sell" and "#CDS buy" are the average number of positions by period. Other statistics correspond to pooled average net exposures by investor and reference sector x region, in €billion.

TABLE VI. Descriptive statistics

Rating	#Ref-Date	CDS sell	CDS buy	Debt long	Debt short	Spread	Basis	CDS bid-ask	Bond bid-ask
$\geq$ aa	38	1.66	-0.87	19.14	-0.08	30.86	-4.07	22.19	0.29
a	196	6.49	-4.27	84.82	-0.24	43.45	2.95	16.41	0.38
bbb	402	13.91	-8.25	91.58	-0.39	71.32	-5.20	11.16	0.39
bb	186	4.01	-2.71	12.60	-0.13	156.99	-24.49	10.48	0.89
b	129	2.91	-1.59	8.77	-0.04	378.70	-10.13	7.72	1.27
$\leq$ ccc	44	0.75	-0.61	0.17	-0.01	643.54	-120.50	13.68	5.38
Default	18	0.06	-0.06	0.57	0.00			27.51	26.09
NA	562	2.35	-0.79	8.22	-0.01	83.58	2.40	18.29	0.49

Notes: Statistics over all reference-dates with at least one non-null exposure in our database. "#Ref-Date" is the number of reference-date unique observations. "CDS sell" and "CDS buy" are the pooled post-2018Q2 average net CDS positions by period. "CDS bid-ask" is computed with CDS spreads in basis points. It is the difference between the bid and the ask spread divided by the mean spread. "Bond bid-ask" is computed with bond prices in percentage. It is the difference between the bid and the ask price divided by the mean price. Both CDS and bond bid-ask are in percentage points with bond bid-ask spreads left-winsorized at 0.

TABLE VII. Descriptive statistics of references

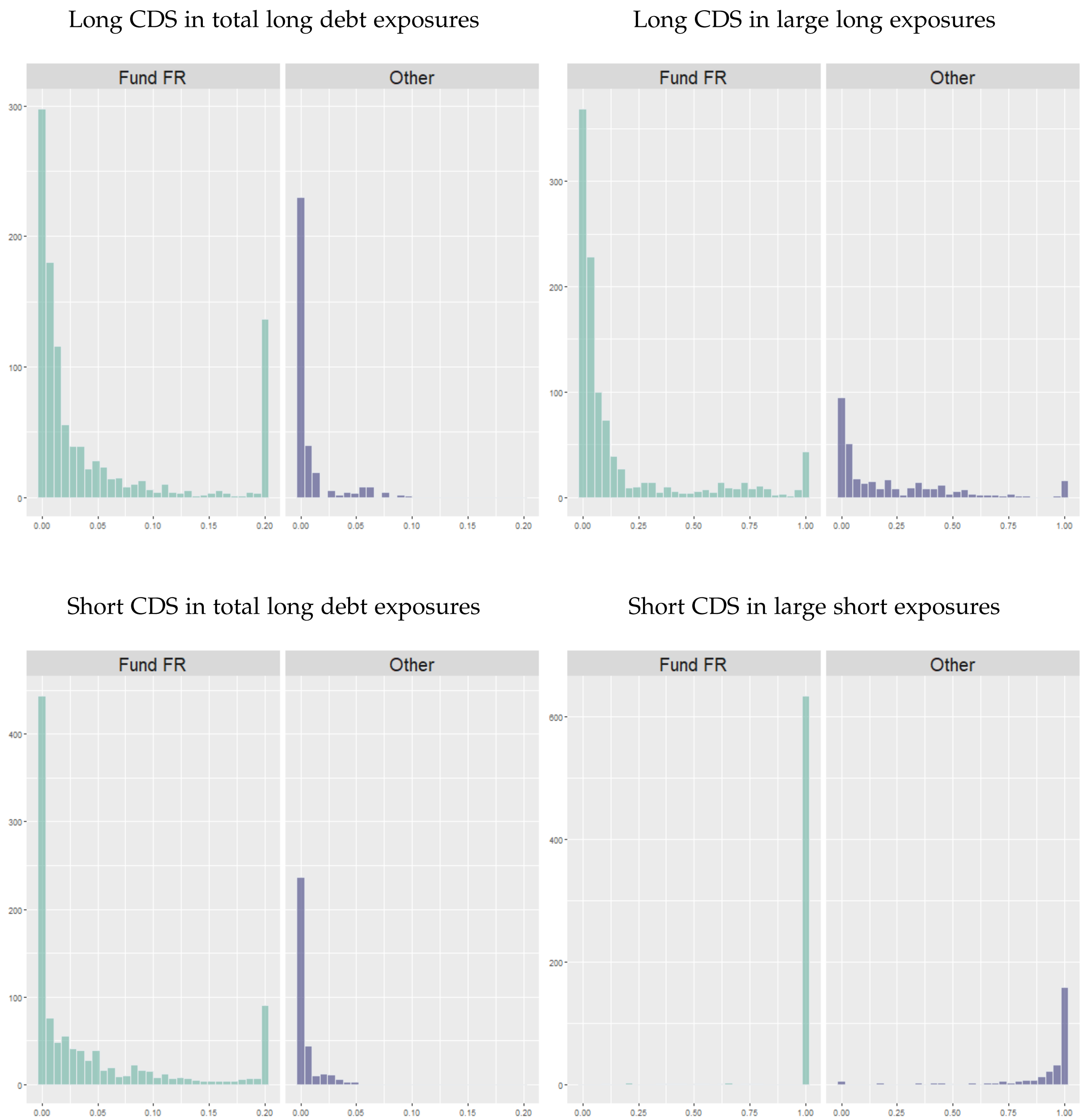

FIGURE VIII. Pooled distribution of the share of CDS positions per reference

Notes: Charts on the left-hand side represent CDS shares of total observed long debt exposures. These distributions are right-censored at 20%. Charts on the right-hand side represent CDS shares of (long or short) total (CDS and debt) exposures to references referencing CDS at least once in our sample. Exposures with no CDS holdings are excluded for readability.

C A methodology to disentangle strategies

C.1 Methodology

Our methodology aims at disentangling speculators, hedgers, and arbitrageurs by exploiting the sign, ratio, and timing of matched debt and CDS positions at the investor-reference-quarter level. In our approach, a trading strategy for CDS_{ijt} is the reason why an investor i holds a CDS on reference j at quarter t. By convention, a negative exposure is short credit risk, and a positive exposure is long credit risk. For ease of notation, we denote a holding $(CDS_{ijt}, Debt_{ijt})$ with a tuple of signs (e.g., $(-,+)_t$), where signs correspond to our convention. An identified strategy is assumed to prevail until either the CDS or the debt position is unwound or changes sign. We proceed with the following steps.

Step 1: We examine whether debt and CDS weakly amplify ($CDS_{ijt} \times Debt_{ijt} \geq 0$) or strictly offset ($CDS_{ijt} \times Debt_{ijt} < 0$) each other. When there is no CDS exposure, the position is *standard*. When CDS and debt exposures amplify each other, investors are considered as *speculators*. Speculators may be *naked* if there is no underlying debt.

Step 2: Among *offsetters*, we single out positions whose hedging ratio is such that $\frac{CDS_{ijt}}{Debt_{ijt}} \leq -2$. These investors are *naked speculators* since the bulk of the CDS creates a negative net position rather than offsets existing debt.

Step 3: We use the timing of entry in positions to disentangle the remaining offsetters for which we observe entry.

Case 1: If the debt position leads the offsetting CDS position (moving from $(+,+)_{t-1}$ or $(0,+)_{t-1}$ to $(-,+)_t$, or symmetrically when hedging a short debt position), then the investor is a *hedger*. This corresponds to the case when hedgers adjust their credit risk position in response to a shock.

Case 2: If both CDS and debt positions are acquired in a single period, moving from $(-,+)_{t-1}$ or $(0,0)_{t-1}$ to $(+,-)_t$, and part of the debt is a loan, then the investor is a *hedger*. This corresponds to the case when hedgers seek to maintain a lending relationship by purchasing a CDS. Therefore, the sequence does not apply to $(-,+)_t$ positions.

Case 3: If both CDS and debt positions are acquired in a single period, moving from $(-,+)_{t-1}$ or $(0,0)_{t-1}$ to $(+,-)_t$, and all debt instruments are debt securities, then the investor is an *arbitrageur* since maintaining a lending relationship can only occur when extending a loan.

Case 4: If both CDS and debt positions are acquired in a single period, moving from $(+,-)_{t-1}$ or $(0,0)_{t-1}$ to $(-,+)_t$, then the investor is an *arbitrageur* regardless of the type of debt instrument used.

Step 4: For offsetters for which we observe exit but not entry, we start by calculating the hedging ratio in the first period of observation (2016Q1). This additional criterion is helpful since investors hedging bonds in response to shocks may exit simultaneously, and therefore be indistinct from arbitrageurs. We use Bayes rule to calculate the probability that the hedging ratio is that of a hedger or an arbitrageur, assuming both strategies have the same unconditional probability,[23] and after estimating the pooled distribution of hedging ratios (HR) for each strategy using a gaussian kernel:

$$\mathbb{P}(Arb|HR) > \mathbb{P}(Hed|HR) \Leftrightarrow \mathbb{P}(HR|Arb) > \mathbb{P}(HR|Hed).$$

Case 1: If the CDS position is unwound before the debt position, moving from $(+,-)_{t-1}$ to $(0,-)_t$ or $(-,-)_t$ or symmetrically for purchasing CDS, then the investor is a *hedger*.

Case 2: If CDS and debt positions are unwound in a single period, moving from $(+,-)_{t-1}$ to $(0,0)_t$ or $(-,+)_t$, and part of the debt is a loan, then the investor is a *hedger*.

Case 3: If CDS and bond only positions are unwound in a single period, moving from $(+,-)_{t-1}$ to $(0,0)_t$ or $(-,+)_t$ or symmetrically for purchasing CDS, then the investor is of the most likely strategy given the hedging ratio as of 2016Q1.

Step 5: All other strategies, for which we observe neither entry nor exit, or for which entry and exit do not follow one of the described patterns, are considered as *others*.

[23] If we use observed unconditional probabilities, hedgers are more likely than arbitrageurs for any hedging ratio.

C.2 Figures

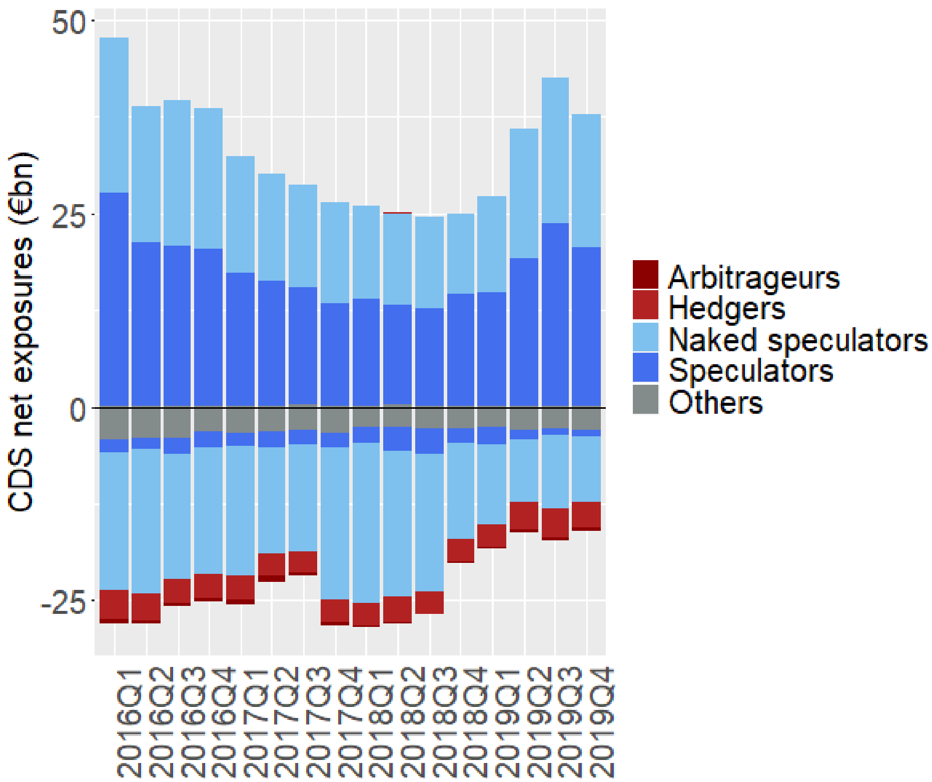

FIGURE IX. Aggregate net exposures by strategy over time

Strategy	#Positions	Debt	CDS	HedgingRatio	ResMat		ShareCCP	Persistence	Turnover	
					Debt	CDS			Debt	CDS
Normal	8044	13.11	0.00	0.00	5.72	2.09	0.05	5.21	0.24	0.00
Others	155	0.45	0.13	0.89	5.17	2.15	0.10	9.76	0.00	0.00
Speculators	716	64.08	28.48	1.82	7.23	2.67	0.17	2.69	1.60	0.67
Naked speculators	1377	0.72	20.04	10.90	8.45	2.48	0.13	3.26	0.10	0.43
Hedgers	197	164.15	17.47	0.26	5.00	2.58	0.11	2.92	0.26	0.86
Arbitrageurs	35	14.68	12.97	1.00	3.37	2.61	0.03	3.29	0.20	0.19

Notes: Statistics are pooled by strategy, irrespective of the sign of the CDS position. "#Position" corresponds to the average number of non-null positions of each strategy by quarter since 2018Q3. "Debt" and "CDS" correspond to the mean face and notional value of a single position, in €mn. "HedgingRatio" is the median absolute hedging ratio $\frac{|CDS_{ijt}|}{|Debt_{ijt}|}$. "ResMatDebt" and "ResMatCDS" are mean residual maturity of debt and CDS in years. "ShareCCP" is the mean notional-weighted share of positions by investor-reference-quarter cleared through a CCP. "Persistence" is calculated as the mean duration of each strategy in our sample in quarters. "TurnDebt" and "TurnCDS" are debt and CDS turnovers within a strategy (intensive margin), calculated as absolute growth rates, trimmed at the 1% level. Note that *naked speculators* include *offsetters* with hedging ratios below -2, hence the non-null debt exposures for this strategy. Also, note that the high persistence of "Others" is attributable to our strategy identification method which requires the observation of entry or exit to allocate positions to specific strategies.

TABLE VIII. Descriptive statistics by strategy

D Remaining tables and figures

	Basis	
	(1)	(2)
Spread	0.084***	0.067***
	(0.008)	(0.008)
Short arbitrage	-13.973**	-19.561***
	(6.732)	(6.775)
Standard long debt	-11.568***	-8.674***
	(2.282)	(2.422)
Standard short debt	-14.497***	-5.663
	(3.837)	(4.129)
Short speculation	-12.091***	-12.322***
	(2.924)	(3.300)
Long speculation	-6.183**	-8.241***
	(3.035)	(3.172)
Long arbitrage	2.606	2.004
	(12.076)	(12.951)
Long offsetting	3.079	-0.718
	(4.326)	(4.844)
CDS bid-ask Ref		-90.277***
		(4.319)
Bond bid-ask Ref		15.768***
		(2.292)
Top1000 CDS liquidity Ref		-3.233**
		(1.342)
Num. Obs.	58,355	47,329
Inv x Quarter FE	Y	Y
Cluster SE	Inv x Q	Inv x Q
Adjusted R^2	0.104	0.122

Notes: Strategy wrt short offsetters other than short arbitrageurs. CDS-bond basis are winsorized at the 1% level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

TABLE IX. CDS bond basis by strategy

	Hedgers, hedging ratio	Speculators, share CDS	
	(1)	(2)	(3)
Share debt exposure	9.216***	−11.046***	−27.773***
	(2.590)	(1.324)	(1.416)
Log Debt	0.113***	−0.106***	
	(0.012)	(0.002)	
Log Total			−0.020***
			(0.002)
Num. Obs.	2,866	9,877	21,650
Inv x Quarter FE	Y	Y	Y
Ref x Quarter FE	Y	Y	Y
Cluster SE	Inv x Q	Inv x Q	Inv x Q
Perimeter	ALL	ALL	ALL
Adjusted R^2	0.743	0.761	0.526

Notes: Sample restricted to non-null CDS positions, with strictly positive debt exposures (columns (1) and (2)), or strictly positive total long credit risk exposures and weakly positive debt and CDS exposures (column (3)). "Hedging ratio" denotes as $\frac{CDS_{ijt}}{Debt_{it}}$. It it negative for hedgers. "Share CDS" stands for $\frac{CDS_{ijt}}{CDS_{ijt}+Debt_{ijt}}$. "Share debt exposure" designates $\frac{Debt_{ijt}}{TotExp_{it}}$. "Log Debt" corresponds to $Log(Debt_{ijt})$. "Log Total" corresponds to $Log(CDS_{ijt} + Debt_{ijt})$. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

TABLE X. Propensity to hedge and speculate at the intensive margin

	Country database				Sector database	
	P(Buy CDS)	P(Sell CDS)	P(Buy CDS)	P(Sell CDS)	P(Buy CDS)	P(Sell CDS)
Share debt exposure	6.22***	9.94***	6.88***	10.83***	7.58***	10.23***
	(1.36)	(1.46)	(1.75)	(1.79)	(1.73)	(1.80)
Log Debt	0.06	−0.15***	0.18***	−0.14***	0.09**	−0.01
	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.05)
Num. obs.	9315	10773	7528	8517	8116	8948
Inv x Quarter FE	Y	Y	Y	Y	Y	Y
Country x Quarter FE	Y	Y	Y	Y	N	N
Sector x Quarter FE	N	N	N	N	Y	Y
Cluster SE	Inv x Q	Inv x Q	Inv x Q	Inv x Q	Inv x Q	Inv x Q
IBP correction	Y	Y	Y	Y	Y	Y
Perimeter	ALL	ALL	NFR Ref	NFR Ref	ALL	ALL

Notes: Logistic regressions on a subsample of long debt investors at country or sector level. "Share debt exposure" designates $\frac{Debt_{ijt}}{TotExp_{it}}$ with j a reference country or sector. "Log Debt" corresponds to $Log(Debt_{ijt})$. The "NFR Ref" perimeter excludes exposures to France. Sectors are considered at the NACE-21 level (codes A to U). Coefficients are corrected from the incidental parameter bias using the methodology developed by Fernández-Val and Weidner (2016). $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

TABLE XI. Probability to buy or sell CDS and concentration of debt exposure at country and sector level

	Δ HHI Inv		Δ Gini Inv	
	(1)	(2)	(3)	(4)
Intercept	0.001	−0.000	0.002**	−0.000
	(0.002)	(0.000)	(0.001)	(0.000)
OtherCDS	0.442***	−0.192	0.124**	−0.128***
	(0.156)	(0.141)	(0.056)	(0.045)
ShortHedger	0.052	−0.239	0.149	−0.130***
	(0.285)	(0.197)	(0.095)	(0.046)
LongSpeculators	−0.425***	−0.221*	−0.320**	−0.227***
	(0.139)	(0.126)	(0.126)	(0.084)
ShortSpeculators	−1.717**	−0.619***	−0.134	−0.134***
	(0.759)	(0.191)	(0.136)	(0.041)
NakedSpeculators	−0.666***	−0.586***	−0.218***	−0.159***
	(0.050)	(0.079)	(0.033)	(0.028)
Num. Obs.	3,171	3,171	3,171	3,171
Investor FE	N	Y	N	Y
Adjusted R^2	0.708	0.872	0.651	0.885
Cluster SE	Inv	Inv	Inv	Inv

Notes: Strategies are continuous variables equal to the share of absolute notional CDS value of each strategy in the sum of total absolute real plus CDS exposure, by investor-quarter. Concentration indices are winsorized at the 5% level. Dependent variables are expressed in percentage change versus the index calculated excluding CDS. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

TABLE XII. CDS trading strategies and changes in HHI and Gini coefficients

	Sell Spread vs Bond Spread
Bank	16.12^{***}
	(2.70)
Dealer	38.44^{***}
	(5.99)
Fund	-1.60
	(5.36)
Insurer	-2.59^{***}
	(0.49)
Num. obs.	607
Cluster SE	Q
Adj. R^2	0.05

Notes: The dependent variable is the notional-weighted spread of CDS sold minus weighted bond spreads, at investor x quarter level. Spreads are right-winsorized at the 1% level. We restrict our analysis to investor-quarters with at least 5 CDS and 5 debt positions. Rating class buckets are the following: $\geq aa$, a, bbb, bb-b, and $\leq ccc$. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

TABLE XIII. Replication of reach for yield result from Jiang et al. (2021)

	HHI Ref				
	(1)	(2)	(3)	(4)	(5)
CDS Ref	0.00	0.00	0.03	-0.00	0.03
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Log Gross debt Ref	-0.02^{***}	-0.02^{***}	-0.02	-0.08	-0.04
	(0.00)	(0.00)	(0.01)	(0.08)	(0.13)
Num. obs.	41392	32466	6575	454	554
Ref FE	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	N	N
Adj. R^2	0.76	0.77	0.79	0.71	0.68
Cluster SE	Ref	Ref	Ref	Ref	Ref

Notes: Reference-level variables have the suffix "Ref". Dependent variables are the HHI at the reference level defined as $HHI_{jt} = \sum_i \left(\frac{|REAL_{ijt}|}{\Sigma_k |REAL_{kjt}|}\right)^2$. "CDS Ref" is a dummy taking value 1 if there is a CDS traded on the reference at a given period. "Log Gross debt Ref" stands for the reference gross debt. The sample includes firms that reference CDS and the 3000 largest ones that do not reference CDS. Specifications (1) is an OLS made on the full sample. Specifications (2) and (3) are staggered difference and difference estimations on the effect of referencing CDS on HHI. Control groups are firms that start (2) or end (3) referencing CDS during the period and treatment groups are firms that never (2) or always (3) reference CDS during the period. Specifications (4) and (5) instead run an event study on ± 4 quarters around the change in CDS referencing for firms that start (4) or stop (5) referencing CDS. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

TABLE XIV. Reference debt concentration (HHI) and CDS referencing

	HHI Inv				
	(1)	(2)	(3)	(4)	(5)
CDS trading	0.00	-0.01	0.01	-0.01	-0.00
	(0.01)	(0.01)	(0.01)	(0.03)	(0.00)
Log Total Exp Inv	-0.03^{***}	-0.03^{***}	0.01	-0.06	-0.01
	(0.00)	(0.00)	(0.02)	(0.04)	(0.01)
Num. obs.	26752	25110	919	125	120
Inv FE	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	N	N
Adj. R^2	0.78	0.76	0.89	0.89	0.99
Cluster SE	Inv	Inv	Inv	Inv	Inv

Notes: Dependent variables are investors HHI defined as $HHI_{it} = \sum_j \left(\frac{|REAL_{ijt}|}{TotExp_{it}}\right)^2$. "CDS trading" is a dummy taking value 1 if the investor is trading at least a CDS at a given period. "Log Total Exp Inv" corresponds to $Log(TotExp_{it})$. The sample includes investors trading CDS as well as those not trading CDS. Specifications (1) is an OLS made on the full sample. Specifications (2) and (3) are staggered difference and difference estimations on the effect of trading CDS on HHI. Control groups are investors that start (2) or end (3) trading CDS during the period and treatment groups are investors that never (2) or always (3) trade CDS during the period. Specifications (4) and (5) instead run an event study on ± 4 quarters around the change in CDS trading for investors that start (4) or stop (5) trading CDS. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

TABLE XV. Investor debt portfolio concentration (HHI) and CDS trading

	Mean spread debt portfolio				
	(1)	(2)	(3)	(4)	(5)
CDS trading	1.09	7.59	-0.89	8.94^{*}	-0.51
	(2.12)	(6.60)	(2.67)	(5.13)	(1.46)
Log Total Exp Inv	-1.52^{*}	-0.24	-6.94^{**}	0.96	-6.49
	(0.79)	(0.70)	(3.49)	(3.79)	(4.59)
Share FR Ref	-11.61^{***}	-9.87^{***}	-12.33	34.31	-61.67^{***}
	(2.54)	(2.24)	(14.70)	(57.81)	(18.51)
Num. obs.	16801	15314	860	102	115
Inv FE	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	N	N
Adj. R^2	0.68	0.69	0.69	0.72	0.78
Cluster SE	Inv	Inv	Inv	Inv	Inv

Notes: The dependent variable is the mean debt portfolio spread in basis points at the investor period level. "CDS trading" is a dummy taking value 1 if the investor is trading at least a CDS at a given period. "Log Total Exp Inv" corresponds to $Log(TotExp_{it})$. "Share FR Ref" is the share of French references in the investor's debt portfolio at a given period. The sample includes investors trading CDS as well as those not trading CDS and it restricts to standard debt or long speculating strategies. Specifications (1) is an OLS made on the full sample. Specifications (2) and (3) are staggered difference and difference estimations on the effect of trading CDS on HHI. Control groups are investors that start (2) or end (3) trading CDS during the period and treatment groups are investors that never (2) or always (3) trade CDS during the period. Specifications (4) and (5) instead run an event study on ±4 quarters around the change in CDS trading for investors that start (4) or stop (5) trading CDS. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

TABLE XVI. Investor debt portfolio spread and CDS trading

	(1)	(2)	Δ VaR (3)	(4)	(5)
CDS trading	-0.0002	-0.0002	0.0001	-0.0003	-0.0002
	(0.0001)	(0.0003)	(0.0004)	(0.0005)	(0.0003)
Log Total Exp Inv	0.0001^{**}	0.0001^{**}	0.0005	-0.0003	0.0006
	(0.0000)	(0.0000)	(0.0003)	(0.0015)	(0.0008)
Num. obs.	27096	25471	912	121	120
Inv FE	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	N	N
Adj. R^2	0.6646	0.6623	0.6979	0.8251	0.6411
Cluster SE	Inv	Inv	Inv	Inv	Inv

Notes: The dependent variable is the portfolio value-at-risk. It corresponds to the 10-day value-at-risk using the filtered historical simulation method. "CDS trading" is a dummy taking value 1 if the investor is trading at least a CDS at a given period. "Log Total Exp Inv" corresponds to $Log(TotExp_{it})$. The sample includes investors trading CDS as well as those not trading CDS. Specifications (1) is an OLS made on the full sample. Specifications (2) and (3) are staggered difference and difference estimations on the effect of trading CDS on HHI. Control groups are investors that start (2) or end (3) trading CDS during the period and treatment groups are investors that never (2) or always (3) trade CDS during the period. Specifications (4) and (5) instead run an event study on ± 4 quarters around the change in CDS trading for investors that start (4) or stop (5) trading CDS. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

TABLE XVII. Investor debt portfolio risk (VaR) and CDS trading