Credit Default Swaps and Credit Risk Reallocation*

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Abstract

Using granular data on both debt and credit default swaps (CDS) exposures by French investors on non-financial corporations (NFC) and euro area banks on French NFCs, we study how CDS reallocate investors' exposure to credit risk. To guide our investigation, we propose a methodology to disentangle investors' strategies between speculators, hedgers, and arbitrageurs. We make three contributions. First, CDS reduce exposure concentration. Hedgers offset their most concentrated exposures while speculators use them as a substitute for debt. Second, speculators use CDS to reach for yield both between and within rating classes. This could pertain to relatively lower leverage constraints at lower ratings, or to the opacity advantage of CDS. Finally, CDS increase investment funds and dealers portfolio risk. Both reach for yield and exposure diversification contribute to this rise. Exposure diversification in the CDS market thus does not translate into return diversification.

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 (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 even facilitate agents' coordination to "bad" equilibria as in Bruneau, Delatte, and Fouquau (2014). These contributions primarily focus on how CDS affect asset prices or reference risk. However, they remain silent on distributional consequences for individual credit 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, Jamilov, Juelsrud, and Rey (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.[2]

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. To guide our empirical investigation, we build a methodology to disentangle and characterize investor strategies by reference and period. There are broadly three motives behind CDS trading: hedging, speculation, and arbitrage. Hedgers use CDS as

[1] Studying credit risk at the individual level 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 [...]".

[2] References using granular data on credit and CDS holdings include Gündüz, Ongena, Tümer-Alkan, and Yu (2017), Czech (2019), Boyarchenko, Costello, and Shachar (2018), Jiang, Ou, and Zhu (2021).

an insurance product to downsize corresponding debt exposures. Conversely, speculators use CDS as an alternative venue to amplify debt exposures or to gain exposure without holding the underlying debt. Finally, arbitrageurs take offsetting positions in CDS and debt to take advantage of relative price discrepancies.

We make three contributions. 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, Eisfeldt, and Weill (2015) predict that hedgers offset their largest debt exposures, but are unable to do so for small exposures in value. On the other hand, theories make opposite predictions regarding speculators' incentives to trade CDS. 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). We confirm Atkeson, Eisfeldt, and Weill (2015) prediction: investors hedge more references for which underlying debt exposures are relatively and absolutely large. Our results also corroborate Oehmke and Zawadowski (2015) views: investors sell more CDS if the reference debt accounts for a smaller proportion of their debt portfolio. Overall, we also find that CDS decrease reference- and investor-level credit risk concentration as measured by the Herfindahl-Hirschman Index (HHI) and the Gini coefficient, with a larger effect for dealers.

Second, we study how speculators use CDS to *reach for yield*. In this context, reaching for yield occurs *between* rating classes, and *within* rating classes (credit rating arbitrage). Investors engage in the former as a result of financial frictions such as moral hazard (Biais, Heider, and Hoerova (2016)), adverse selection, or counterparty risk externality (Acharya and Bisin (2014)). CDS relative opacity may exacerbate these frictions and encourage investors to sell relatively more CDS on riskier references. Another explanation could be that CDS margin requirements are relatively low for poorer ratings. In addition, rating-based capital requirements or investment mandates increase investors' propensity to engage in credit rating arbitrage, i.e. to invest in the highest-yielding references for a given rating (Becker and Ivashina (2015)). We find evidence that investors reach more for yield with CDS than with debt both between and within rating classes. Indeed, the share of CDS in investors exposure increases for references with lower ratings, in all investment sectors. Within a rating class, all investors' cross-border CDS strategies exhibit higher spreads than those relying on debt only, suggesting CDS are more subject to credit rating arbitrage.

Overall, accounting for CDS may have an ambiguous effect on portfolio risk. While a reduction in credit risk concentration brings diversification benefits, reaching for yield relates to higher portfolio risk. In our third contribution, we show that CDS translate into higher portfolio risk for dealers and investment funds, as measured by portfolio volatility and Value-at-Risk (VaR). While reach for yield unsurprisingly correlates to this increase, exposure diversification also positively contributes. Exposures diversification from CDS thus does not entail return diversification of investors portfolio.

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, Eisfeldt, and Weill (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, Ou, and Zhu (2021) who explore US mutual funds liquidity and risk-taking motives, or Gündüz, Ongena, Tümer-Alkan, and Yu (2017) who show that higher standardization of CDS fosters higher hedging by German banks.

To the best of our knowledge, we are also the first paper to examine how single-name CDS affect individual portfolio risk. In this respect, our paper is at the crossroads of papers on how different asset classes contribute to portfolio risk (Hippert, Uhde, and

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

Finally, we add to the literature on the motives and consequences of reach for yield. This question has been studied extensively in the debt market by *inter alia* Becker and Ivashina (2015) (for insurance), Choi and Kronlund (2018) (for investment funds), or Boermans and van der Kroft (2020) (for all investment sectors). In the CDS market, we complement the unique study to date on this topic by Jiang, Ou, and Zhu (2021).

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 three main contributions, and Section 5 concludes.

2 Data

2.1 Credit default swaps

Investors can choose between two instruments to gain credit 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 such that the 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.

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

2.2 Data collection

Banque de France grants access to supervisory granular 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 national registers, *OPC titres* and *Solvency 2*, report holdings at the ISIN level of respectively French investment funds and French insurers. *SHS-G* instead provides granular holdings of securities by EA banks. We restrict these holdings to debt securities with a valid nominal. Loans from French registered banks to NFCs are drawn from the French credit register *SCR*. Finally, we use data provided by 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. We uniquely identify issuers of securities and loans leveraging an enriched version of Eurosystem identification databases (*RIAD* and *CSDB*).[4]

We aggregate quarterly exposures from investors to references by instrument type. We also collect ancillary data on investors and references. Reference ratings are collected from *CSDB*. *Eikon* provides most of the references CDS spreads, and a measure of the CDS-bond basis. We also collect quarterly public CDS liquidity data on the top 1000 most traded references from DTCC. Finally, we add references balance sheet and P&L data from the French register of firms, *FIBEN*, and *Eikon*. Appendix A provides more details to the cleaning procedure.

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 (i.e., credit valuation adjustment). In the main part of the paper, we focus on single-name CDS. We provide additional results

[4]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 the ESCB statistics. We enrich them with several complementary data sources: GLEIF for LEI, national registers on parent relationships between NFCs, and manually identify any remaining ISIN.

with CDS indices in the online appendix.

The final dataset presents an 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 also neglect EA banks cross-border lending to French NFCs, which is negligible in front of debt securities.[5]

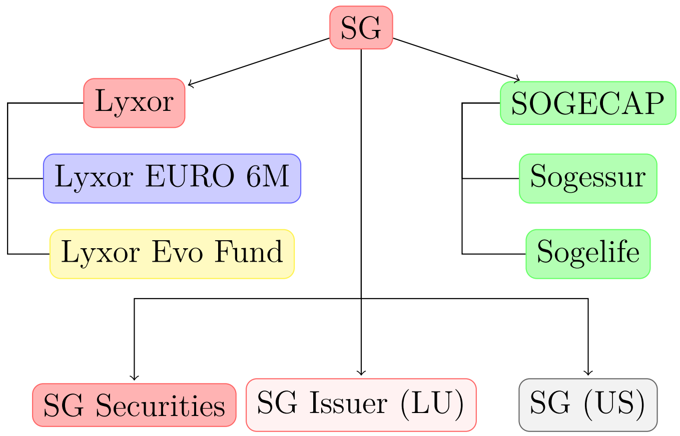
2.3 Our approach to consolidation

Banks and insurers are consolidated according to prudential perimeters, while investment funds are left unconsolidated. Indeed, banks and insurers are subject to different legal frameworks and consequently to separate reportings and risk management strategies even if they belong to the same conglomerate. Doing so, we neglect any conglomerate level risk management strategy. Investment funds are consolidated separately since asset managers and shareholders generally do not coincide. Asset managers are only exposed to funds performance through fees and commissions, and with limited liability. Beyond these constraints, we consolidate exposures at the highest possible level since risk management is generally undertaken at the group level to manage risks arising from lending and investment activities at the entity level. Hence we remove intragroup holdings.

Figure 1 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 stylized 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.

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

[5] As of end-2019, cross-border lending represents 7% of loans to French NFCs in national accounts.



Bank affiliated entities for which we have all exposures are filled in red. We miss loan exposures from light red banks in the EA, and we do not have any information from non-EA banks in grey. Insurers affiliated entities are in green. Funds are kept separate, with distinct colors.

Figure 1 – Stylised consolidation for Société Générale

group. However, limited liability clauses within a group may still distort our observation of real exposures.

One limitation to our approach is that we do not observe holdings of non-EA bank subsidiaries, as well as loans by non-French bank subsidiaries. Therefore, risk management at the French banking group level may occur in relation to unobserved debt holdings. Our observation of bank non-French debt holdings is thus subject to a downward bias. When appropriate, we restrict our analyses to French lenders and borrowers only where the bias should be mildest. We also provide additional results at the unconsolidated level in an online appendix.

2.4 Sample overview by investor

Table 9 presents the number of positions and their size averaged across periods. By convention, 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, 35 EA banks (of which 3 French, and 1 non-French dealer), 3 French dealers[6], and 3 French insurers. Dealers account for the

[6]The group of the sixteen largest derivatives dealers (G16) includes Bank of America, Barclays, BNP

lion's share of CDS positions. They sell (buy) on average €26.8bn (18.2) single-name CDS, compared to €3.5bn (2.2) for funds, €2.6bn (3.3) for banks, and €0.8bn (0.05) for insurers. Banks and dealers lend €104.8bn to NFCs in the sample. Total average bond exposures stand at €114.6bn, of which insurers hold half. Because lending is essentially a domestic activity, investors lend more to French references (€101.9bn) than to non-French ones (€2.9bn). However, they hold more bonds on non-French references - €86.8bn against €27.8bn. CDS trade on respectively 69 and 910 French and non-French NFC references. We observe a total of 35,581 investor-reference pairs over our sample. Figure 5 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 2019$Q4$. Although single-name CDS represent a small fraction of aggregate long credit risk exposures, their contribution to exposures to large firms whose idiosyncratic shocks may matter for aggregate outcome is important.

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, Costello, and Shachar (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, Eisfeldt, and Weill (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

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.

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. Che and Sethi (2014) contend that leverage constraints are looser for selling CDS than for purchasing bonds on margin. Jiang, Ou, and Zhu (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 2016$Q1$, we exploit exit patterns and relative hedging ratios for identification. These latter are 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, either 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. This 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.

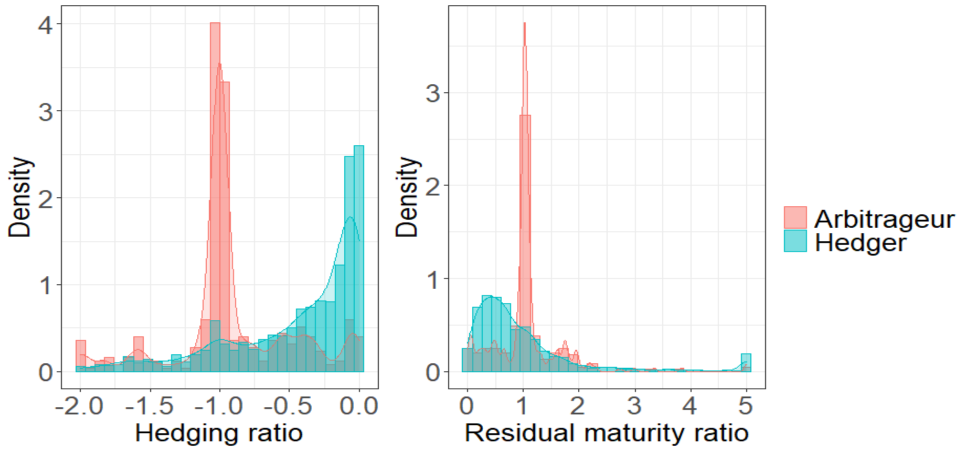
3.2 Hedgers vs Arbitrageurs

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 2 represents the pooled distribution of each strategy's hedging ratio (on the left-hand side), and residual maturity ratio[7]. 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 22%, while the mean residual maturity ratio is around 0.5 years.

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[8]. Assuming arbitrageurs have a relative advantage in managing those risks, the more negative the basis, the more profitable the arbitrage

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

[8]Bond collateral value variation, bond liquidity risk, investor funding risk, and counterparty risk in the CDS market.



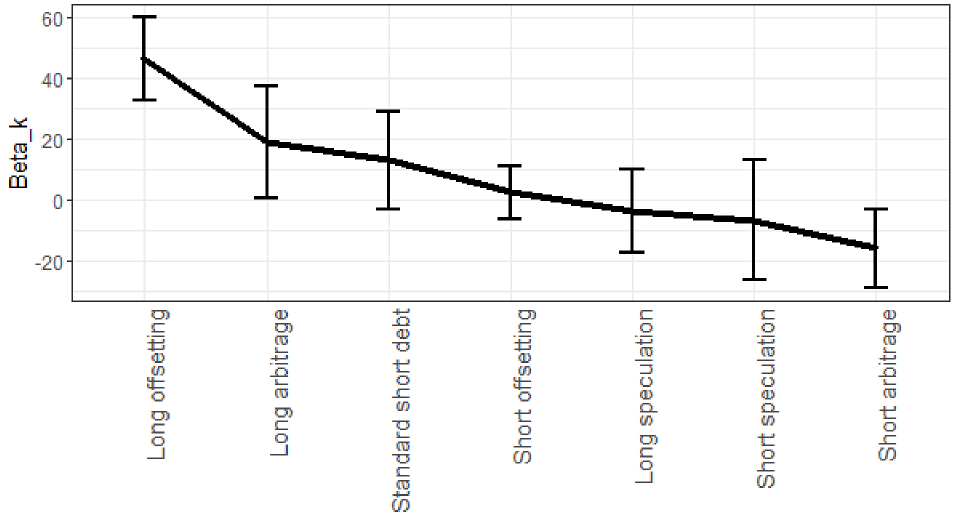
Note: Distributions before the identification of offsetters already existing as of 2016Q1 (step 4 of the methodology described in Appendix C.1). By convention, purchasing a CDS gives rise to a negative CDS position hence the negative hedging ratio. Residual maturity $RESMAT$ is the average maturity for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

Figure 2 – Pooled distribution of hedging ratios $\frac{CDS_{ijt}}{Debt_{ijt}}$ (lhs) and residual maturity ratios $\frac{RESMAT\_CDS_{ijt}}{RESMAT\_Debt_{ijt}}$ (rhs) for hedgers and arbitrageurs purchasing CDS

strategy. We formally test whether CDS subject to arbitrage strategies exhibit a different basis with Equation 1.

$$CDSBondBasis_{ijt} = \alpha Spread_{jt} + \sum_{k} \beta_k Strategy_{ijt}^{k} + FE_{it} + \epsilon_{ijt}, \qquad (1)$$

with $Spread_{jt}$ the reference CDS spread to control for credit risk, and FE_{it} investor-quarter fixed effects. Figure 3 plots the coefficients associated with each strategy. Arbitrage strategies combining a CDS and a bond purchase (*short arbitrage*) involve CDS with the lowest basis. In particular, this basis is statistically lower for arbitrageurs than for other offsetting strategies involving the purchase of a CDS (*short offsetting*). *Long arbitrage* strategies, despite the small number of observations, have a relatively high basis. Taken together, these analyses make us confident hedgers and arbitrageurs have different trading motives.



Note: 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. Data contains 496 short arbitrageurs and 9 long arbitrageurs. Speculators include naked speculators.

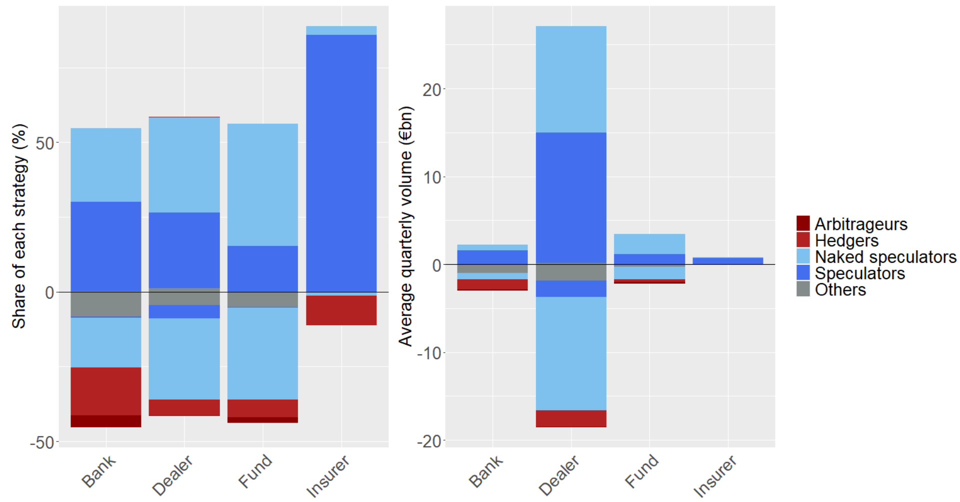
Figure 3 – Mean CDS-bond basis by strategy vs *standard long debt*

3.3 Trading strategies in the sample

Figure 4 plots the distribution and notional amounts by strategy. Overall, dealers represent the bulk of exposures with 80% of notional CDS exchanged (resp. 59% 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 6 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 10 of 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 shows that a large percentage of CDS purchased do not offset preexisting debt exposures: between 58% for banks, 79% for funds, 90% for dealers. Therefore, although CDS remain a zero-sum game who do not change aggregate returns, they increase the sum of individual exposures at default.



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

Figure 4 – Pooled distribution (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. On top of that, CDS decrease the concentration of credit risk, measured by the HHI or Gini coefficient, both at the investor and reference level.

According to Atkeson, Eisfeldt, and Weill (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.[9] Two alternate views emerge from the literature on speculators. According to Che and Sethi (2014), speculators sell CDS

[9]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.

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, 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 specific strategies, as specified in equation 2:

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

where Y_{ijt} is a dummy for speculating or hedging, and X_{ijt} a set of investor-reference-quarter controls. 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. For speculator strategies, if CDS are a complement (resp. a substitute) for debt, then β is positive (resp. negative). If predictions from Atkeson, Eisfeldt, and Weill (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. What matters is relative demand for such CDS from different investors. Symmetrically, we use investor-quarter fixed effects to control for entity-level risk demand and focus simply on how relative risk concentration determines demand for CDS.

Table 1 presents the baseline results. We restrict the sample to investors holding a positive amount of debt. To purge out any unobservable at the investor or reference level, both investor- and reference-quarter fixed effects saturate the regression.[10] Results from the first column support the predictions from Atkeson, Eisfeldt, and Weill (2015): hedgers offset their exposures representing a large share of their portfolio and with large values. On average, the odds ratio of hedging increases by 82% when the share of debt exposure increases by 1pp, while that of speculation decreases by 114%. Hedgers incentives stand

[10]For instance, exposures may be more concentrated on smaller more opaque references due to information asymmetries.

in contrast with those of other CDS purchasers, who do not appear motivated by debt concentration in column (2). Our results are robust to a number of alternative specifications presented in Table 11. However, at odds with theory, we also show that the opposite goes for the intensive margin. Conditional on purchasing CDS, hedging ratios are smaller for more concentrated exposures, even controlling for exposure value. This suggests the presence of convex costs of hedging.

Column (3) shows that the probability to sell CDS on a reference conditional on holding its debt is lower when the share of debt in investors portfolio is high. This result confirms predictions from Oehmke and Zawadowski (2015): speculators use CDS as an alternative trading venue for debt, irrespective of absolute position size position. This result is also robust to alternative specifications presented in Table 12 in the Appendix. Here, results also hold at the intensive margin. Not only do investors speculate less on concentrated debt exposures, but when they do so, they tend to sell relatively fewer CDS.

Our results on hedging are consistent with Gündüz, Ongena, Tümer-Alkan, and Yu (2017) who find that German banks increased hedging on larger and riskier exposures after the CDS "Small Bang". Our analysis corroborates these results on a larger set of financial institutions and emphasizes how debt concentration is the primary driver of hedging. Regarding speculation, we add to Acharya, Gündüz, and Johnson (2018) who showed how German banks less exposed to peripheral European sovereign CDS increased CDS selling most throughout the European sovereign crisis.

Since CDS allow both hedgers and speculators to decrease portfolio concentration, they should decrease aggregate credit risk 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. Larger indices indicate higher levels of credit risk concentration. Investor-reference exposures

	P(Hedger)	P(Buy CDS and Non hedger)	P(Speculator)
Share debt exposure	39.03^{***}	-22.91	-27.00^{***}
	(10.00)	(15.20)	(7.59)
Log Debt	0.43^{***}	0.29^{***}	-0.01
	(0.04)	(0.05)	(0.02)
Num. obs.	13496	9264	28970
Inv x Quarter FE	429	329	667
Ref x Quarter FE	1652	1703	3929
Cluster SE	Inv x Q	Inv x Q	Inv x Q
IBP correction	Y	Y	Y

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Logistic regressions on a subsample of long debt investors. "Share debt exposure" designates $\frac{Debt_{ijt}}{TotExp_{it}}$. "Log Debt" corresponds to $Log(Debt_{ijt})$. Coefficients are corrected from the incidental parameter bias using the methodology developed by Fernández-Val and Weidner (2016).

Table 1 – Probability to enter strategies and concentration of debt exposure

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:[11]

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

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 Gini indices by estimating equations 3 for investors and 4 for references (with analog

[11]The HHI and Gini coefficient 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.

equations for Gini coefficients):

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

and:

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

with investor sector $SECTOR_i$, and $I(FR)_j$ a dummy for French references.

Table 2 presents the results and confirms that CDS decrease the concentration of credit risk among investors. This finding is valid with both HHI and Gini coefficient. The effect of CDS on portfolio concentration is the largest for dealers, with a 42% (HHI) and 10% (Gini) drop in concentration indices. CDS also decrease the concentration of banks and funds portfolios but the magnitude of the effect is smaller with 7% (resp. 4%) for banks (resp. funds). Likewise, CDS on average increase the set of investors exposed to a reference. They decrease references HHI by 9% for non-French and by 2% for French references. Unsurprisingly, the effect is stronger for non-French references, since their debt holdings are biased downwards in our data.

4.2 CDS are used to reach for yield

In this section, we investigate how investors use CDS to reach for yield, both *between* and *within* rating classes. We show that CDS usage is higher on lower-rated references, and higher-yielding references in each rating class. French speculators have a higher propensity to perform rating class arbitrage than non-French speculators.

We refer to *reach for yield* to designate the two following behaviors. First, CDS opacity[12] may exacerbate financial frictions and aggravate risk-taking incentives.[13] In

[12] Jiang, Ou, and Zhu (2021) give three reasons why CDS may be more opaque than bonds, the second one being obsolete: (1) Derivatives are not included in most processed holdings databases; (2) Before the SEC specified the rules of cash collateral segregation for CDS short positions in 2012, there was no clear metric go gauge the level of implied leverage; (3) CDS do not affect risk metrics calculated with market value since their market value is close to zero.

[13] A large literature explores how financial frictions give rise to risk-taking incentives. See for instance Biais, Heider, and Hoerova (2016) for moral hazard, Thompson (2010) for moral hazard and adverse selection, or Acharya and Bisin (2014) for counterparty risk externality, among many others.

	HHI Inv (1)	HHI Ref (2)	Gini Inv (3)	Gini Ref (4)
Bank	-0.07^{**}		-0.03^{***}	
	(0.03)		(0.01)	
Dealer	-0.42^{***}		-0.11^{***}	
	(0.05)		(0.02)	
Fund	-0.03^{***}		-0.01^{***}	
	(0.01)		(0.00)	
Insurer	0.00		0.00	
	(0.01)		(0.00)	
Non FR Ref		-0.12^{***}		-0.05^{***}
		(0.01)		(0.00)
FR Ref		-0.04^{***}		-0.02^{***}
		(0.02)		(0.00)
Num. obs.	3091	11774	3091	11641
Quarter FE	Y	Y	Y	Y
Cluster SE	Inv	Inv	Inv	Inv
R^2	0.19	0.01	0.12	0.03

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Differences in HHI or Gini are censored at the 95% level. Reference-level variables have the suffix "Ref".

Table 2 – Aggregate effect of CDS on credit risk concentration: changes in HHI and Gini coefficients

addition, CDS relative liquidity may be higher for riskier references for which debt issues are more fragmented, and debt trades smaller.[14] In these cases, investors would have incentives to use CDS to reach for yield between rating classes. Second, rating-based regulatory requirements or investment mandates[15] may incentivize investors to reach for yield within rating classes, that is invest in the highest yielding references by rating class. Indeed, spread distributions by rating class partially overlap as Figure 7 illustrates on our sample. As argued in Becker and Ivashina (2015), ratings primarily reflect probabilities of default and losses given default, but not the associated risk premia.[16] Literature on

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

[15]Choi and Kronlund (2018) state that "investment mandates of corporate bond funds often guide the maturities and credit ratings of the securities that they seek to invest in".

[16]They also tend to be updated slowly (Cornaggia and Cornaggia (2013), and can be subject of agency conflicts (Becker and Milbourn (2011)).

regulatory arbitrage has evidenced such behaviors with debt on highly regulated industries such as banks and insurers (Becker and Ivashina (2015), Boermans and van der Kroft (2020)), or money market funds (Di Maggio and Kacperczyk (2017)). Choi and Kronlund (2018) also show that while investment funds do not reach for yield on average, they tend to reach for yield more in low-interest rate environments. We investigate whether CDS are used to reach for yield between and within rating classes in turn.

Do long credit risk investors increasingly resort to CDS as credit ratings deteriorate? Jiang, Ou, and Zhu (2021) indirectly suggest this is the case for US mutual funds over the 2006-2012 period, by showing that their notional-weighted CDS sell spreads are significantly larger than their weighted bond spreads. We first replicate their analysis on our universe of French investors and exposures. Column (1) of Table 13 confirms the finding: the mean difference between CDS and bond spreads at the investor-quarter level stands at 18bps for banks and 42bps for dealers, while investment funds exhibit a 37bps difference - compared with 93bps put forward in Jiang, Ou, and Zhu (2021).

To complement this analysis, we estimate the composition of speculators credit risk exposure by rating, as specified in Equation 5:

$$ShareCDS_{ijt} = \Lambda\Big(\sum_r \beta_r Rating^r_{jt} + X_{ijt} \Big) + \epsilon_{ijt}, \tag{5}$$

with $ShareCDS_{ijt}$ the share of CDS in credit risk exposure for the investor-reference pair, $Rating_{jt}$ reference j rating at period t, and X_{ijt} a set of investor-reference-quarter controls. Table 3 presents the results. Columns (1) and (2) show that the share of CDS in credit risk exposure increases as credit quality deteriorates. This holds up until bb-rated references, while CDS usage used is highest for $\leq ccc$-rated references.[17] These results hold after controlling for simple measures of CDS and bond liquidity, respectively a dummy for references belonging to the top 1000 most traded CDS, and outstanding reference gross debt. This suggests that reach for yield motivates CDS speculation beyond relative

[17] We excluded references in default for which CDS positions are likely to reflect post-default trades where residual uncertainty comes from settlement risk rather than credit risk.

liquidity of debt and CDS. Quantitatively, the share of CDS in credit risk exposures is 2 to 3pp higher for a bb-rated reference than for $\geq aa$-rated references.

Two mechanisms could account for this behavior. First, opacity may make CDS relatively attractive to boost returns while safeguarding fund metrics. By a similar token, Chen, Cohen, and Gurun (2021) find that bond fund managers misclassify the risk of their holdings to attract higher investment flows. Second, the difference between bond haircuts and CDS margins may provide a relative advantage to CDS for lower credit ratings.

	CDS share			
	(1)	(2)	(3)	(4)
a	0.26^{***}	0.01^{***}	0.24^{***}	0.01^{**}
	(0.08)	(0.00)	(0.08)	(0.00)
bbb	0.60^{***}	0.03^{***}	0.52^{***}	0.03^{***}
	(0.08)	(0.01)	(0.09)	(0.00)
bb	0.48^{***}	0.02^{***}	0.54^{***}	0.03^{***}
	(0.10)	(0.01)	(0.11)	(0.01)
b	0.18	-0.01	0.23^{**}	-0.00
	(0.11)	(0.01)	(0.11)	(0.01)
<=ccc	0.97^{***}	0.09^{***}	1.29^{***}	0.13^{***}
	(0.17)	(0.02)	(0.21)	(0.02)
Log Total	0.00	-0.01^{***}	-0.09^{***}	-0.01^{***}
	(0.02)	(0.00)	(0.02)	(0.00)
FR Ref	-1.12^{***}	-0.05^{***}	-0.97^{***}	-0.05^{***}
	(0.14)	(0.01)	(0.12)	(0.01)
CDS liquidity Ref			1.30^{***}	0.08^{***}
			(0.05)	(0.01)
Log Gross debt Ref			-0.04^{***}	-0.00^{***}
			(0.01)	(0.00)
Num. obs.	49070	85533	46794	82362
Inv x Quarter FE	Y	Y	Y	Y
Cluster SE	Inv x Q	Inv x Q	Inv x Q	Inv x Q
Model	Logit	Panel	Logit	Panel

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Regressions on a subsample of long credit risk speculators with respect to references rated $\geq$ aa. Reference-level variables have the suffix “Ref”. ”Log Total” refers to total (CDS and debt) credit risk exposures. ”CDS liquidity Ref” is a dummy taking value 1 for the top 1,000 most liquid references as reported by DTCC.

Table 3 – Share of CDS usage by rating for speculators

We now turn to the question of whether CDS are more used than debt to take advantage of rating-based rules or regulation, which we alternatively refer to as credit rating arbitrage. Jiang, Ou, and Zhu (2021) contrast CDS sellers that invest in the highest spreads by rating category, with CDS buyers that exhibit a more even distribution of spreads.[18] However, there must be some investment sector or geography counterpart to these transactions. We first replicate their analyses and show that reach for yield within rating classes across sectors is more nuanced in France. Columns (2) and (3) of Table 13 confirm that funds sell CDS on the highest yielding references by rating class. Dealers both sell and purchase CDS on higher spreads than average, while banks do the opposite.

We build upon our methodology to investigate whether investment strategy predicts rating arbitrage. We discriminate between long and short speculators (including naked ones), standard (long or short) debt investors, short hedgers, and other strategies involving CDS trading. As specified in Equation 6, we compare the propensity of each type of investor to reach for yield:

$$Y_{ijt} = f\left(\sum_r \beta_r Strategy^r_{ijt} + Rating_{jt} + X_{ijt}\right) + \epsilon_{ijt}, \tag{6}$$

with $Strategy_{ijt}$ the investor-reference-quarter strategy, X_{ijt} a set of investor-reference-quarter controls, f either a linear or a Logit model, and Y_{ijt} the severity of rating arbitrage. We consider two proxies. First, we assess investors propensity to invest in higher spreads by rating class. To do so, we normalize spreads by rating class since their dispersion increases when ratings deteriorate. Then, we follow Boermans and van der Kroft (2020) methodology to derive an overrating probability for each reference-quarter. This is tantamount to calculating the probability that, given its spread, a reference belongs to the rating class immediately below. Using Bayes' rule and assuming ratings can only be one notch off, the probability of being overrated is derived in Equation 7:[19]

[18] Specifically, Jiang, Ou, and Zhu (2021) show that CDS sellers invest in the highest available spreads within high-yield and investment-grade categories, and in the highest quartiles of the spread distributions within four rating notch categories.

[19] A detailed account of our methodology can be found in Appendix D.

$$P(Rating_{below,jt}|Spread_{jt}) = \frac{P(Spread_{jt}|Rating_{below,jt}) * P(Rating_{below,t})}{\sum_{k \in \{below,exact,above\}} P(Spread_{jt}|Rating_{k,jt}) * P(Rating_{k,t})}, \tag{7}$$

with $Rating_{below,jt}$ a dummy taking value 1 if reference j belongs to the rating below. The first two columns of Table 4 provide the results of these estimations. All strategies involving CDS trading exhibit higher spreads than standard debt strategies for a given rating. This suggests credit rating arbitrage is more pronounced in the CDS than in the debt market. Columns (3) and (4) restrict the analysis to standard debt and long speculator strategies to analyze sectoral patterns. It appears that funds and dealers reach for yield most among speculators, consistent with our replication of Jiang, Ou, and Zhu (2021). In Table 14, we further breakdown the results by country of residence of both investors and references. Column (2) shows that domestic CDS exposures of French investors exhibit no sign of overrating, while the reverse goes for all cross-border exposures of French investors. Long speculators use CDS as an alternative trading venue to reach for yield on non-French references. Short speculators and short hedgers are then their potential counterparts. We also find that non-French speculators trade on unusually high spreads on French counterparts, although the coefficient is lower and the significance does not extend to CDS purchasers.

	Normalized spread	P(overrated)	Normalized spread	P(overrated)
	(1)	(2)	(3)	(4)
Long Speculators	0.17^{***}	0.19^{***}	0.11^{***}	0.19^{***}
	(0.02)	(0.04)	(0.02)	(0.05)
Short Speculators	0.14^{***}	0.13^{***}		
	(0.01)	(0.04)		
Short Hedger	0.09^{***}	0.05		
	(0.02)	(0.06)		
Other CDS	0.08^{***}	0.02		
	(0.03)	(0.08)		
Dealer			-0.00	0.08
			(0.03)	(0.06)
Fund			0.01	0.07
			(0.02)	(0.05)
Long Speculators:Dealer			0.09^{**}	0.06
			(0.03)	(0.06)
Long Speculators:Fund			0.04^{**}	0.07
			(0.01)	(0.05)
Log Gross debt Ref	0.05^{***}	0.20^{***}	0.06^{***}	0.21^{***}
	(0.00)	(0.01)	(0.01)	(0.02)
CDS liquidity Ref	-0.19^{***}	-0.50^{***}	-0.16^{***}	-0.45^{***}
	(0.02)	(0.03)	(0.05)	(0.09)
Num. obs.	90572	90387	73647	73499
Inv x Quarter FE	Y	Y	N	N
Quarter FE	N	N	Y	Y
Ref Rating FE	Y	N	Y	N
Cluster SE	Inv x Q	Inv x Q	Q	Q
Model	Panel	Logit	Panel	Logit

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Columns (1) and (2) are wrt strategies with no CDS (long or short debt only). Columns (3) and (4) are wrt strategies with no CDS, filtering out all CDS trading strategies other than long speculators, as well as insurers. Reference-level variables have the suffix "Ref". "Long speculator" designates strategies with (weakly) positive bond and (strictly) positive CDS exposures, and symmetrically for "Short speculator". "Normalized spread" is the difference between the spread and mean spread by rating, normalized by the spread standard deviation by rating. Sector effects are wrt banks. "Log Total debt Ref" designates the reference total debt held by investors in the database. "CDS liquidity Ref" is a dummy taking value 1 for the top 1,000 most liquid references as reported by DTCC.

Table 4 – Credit rating arbitrage by trading strategy and investor sector

4.3 CDS have heterogeneous effects on portfolio risk

Our analyses suggest that accounting for CDS has an ambiguous effect on individual risk. CDS are used to reach for yield, but also contribute to asset diversification. In this section, we evaluate these offsetting effects and how they ultimately contribute to portfolio risk. Funds and dealers portfolio risk is higher when accounting for CDS, and reaching for yield strategies contribute to an increase in portfolio risk. However, asset diversification does not entail portfolio return diversification. Lower Gini coefficient and HHI attributable to CDS trading translate into higher portfolio risk.

Specifically, we examine how portfolio risk metrics change when accounting for CDS. Our approach builds on a literature measuring how different asset classes contribute to portfolio risk (see for instance Hippert, Uhde, and Wengerek (2019) for CDS indices, or Bessler and Wolff (2015) for commodities). We focus on two standard risk metrics. First, we examine daily portfolio variance, which is traded off with returns in Markowitz (1952) model with CARA utility. Then, we analyze 10-days VaR, a standard measure of portfolio risk at least since Linsmeier and Pearson (2000). As discussed in Pritsker (2006) or Kuester, Mittnik, and Paolella (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, Giannopoulos, and Vosper (1999). It consists of filtering out shocks from an $ARCH(1,1)$-specified history of returns, and simulating 10-days ahead.

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

$$r_{j,t} \approx -(Spread_{j,t} - Spread_{j,t-1})\left(T - \frac{1}{250}\right) + \frac{Spread_{j,t}}{250}, \tag{8}$$

with $Spread_{j,t}$ the par-spread of reference i on date t and T its remaining time to maturity.[20] The first term corresponds to the change in the CDS par market value, which

[20]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.

benefits decreasingly to the seller as maturity approaches. The second term refers to interests accruing to the seller. Additionally, we assume the CDS-bond basis is null, 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 - since 5-year CDS contracts are the most prevalent.

Table 5 presents how CDS alters portfolio risk by investor sector. We define the CDS Intensity as the ratio of the number of CDS positions to the total number of positions at the investor-quarter level. CDS are expected to change portfolio's risk for investors with high CDS intensity. CDS trading intensity increases volatility and VaR for all investment sectors, and most so for investment funds. This is consistent with the fact that banks use CDS the most for hedging. These results continue to hold for funds and to some extent for dealers within investor (after controlling by investor fixed effects) in Table 15.

To confirm this interpretation, Table 16 in the Appendix investigates how the intensity of different strategies at the investor-quarter level relates to risk-taking. Short speculation systematically relates to higher portfolio risk. Long speculation as well, although the result only holds across investors: the intra-investor variation in long speculation intensity does not relate to any change in risk. This could be an artefact of the limited variation in time of long speculation positions. Finally, hedging always relates to lower portfolio risk.

Finally, Table 6 directly relates exposure concentration and reach for yield intensity to portfolio risk at the investor-quarter level. Reach for yield intensity is captured by the mean overrating probability of long speculative strategies at the investor-quarter level (to measure rating class arbitrage intensity), and the change in the share of high-yield exposures due to long speculative strategies at the investor-quarter level (to measure reach for yield between rating classes). We find that rating class arbitrage significantly contributes to portfolio risk while reaching for yield between rating classes does so non-significantly. Perhaps surprisingly, we also find that exposure concentration *negatively* contributes to portfolio risk. Although CDS reduce investors portfolio concentration, they do not translate into higher return diversification.

	Dependent variable:			
	Count		Value	
	Δ Vol	Δ VaR	Δ Vol	Δ VaR
	(1)	(2)	(3)	(4)
Bank:CDS Intensity	0.563^{**}	0.118^{***}	1.006^{**}	0.220^{**}
	(0.244)	(0.042)	(0.472)	(0.087)
Dealer:CDS Intensity	1.210	0.156^{***}	1.807^{*}	0.210^{***}
	(0.828)	(0.050)	(0.946)	(0.025)
Fund:CDS Intensity	2.952^{**}	0.332^{***}	2.355^{**}	0.304^{***}
	(1.366)	(0.101)	(0.920)	(0.085)
Insurer:CDS Intensity	−0.022	−0.053	−0.774	−0.564
	(0.250)	(0.040)	(1.198)	(0.460)
Num. obs.	3,129	3,108	3,129	3,108
Adjusted R^2	0.025	0.111	0.025	0.138
Quarter FE	Y	Y	Y	Y
Cluster SE	Inv	Inv	Inv	Inv

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. We winsorize risk metrics at 1% level. In columns (2) and (3), CDS Intensity stands as the ratio of the number of CDS positions to the total number of positions at the investor-quarter level. In columns (4) and (5), it is measured as a ratio of absolute credit risk exposures. Dependent variables are the difference in percentage (for volatility) or percentage points (for value-at-risk) between portfolios with CDS and portfolios without CDS. We change the sign of value-at-risk difference to give the same sign interpretation to volatility and value-at-risk changes. "Δ VaR" corresponds to the 10-day value-at-risk using the filtered historical simulation method. 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.

Table 5 – Effect of CDS on portfolio risk by sector

4.4 Discussion

Throughout the paper, we implicitly take outstanding reference debt and investors' debt exposures as given. This follows a theoretical (Atkeson, Eisfeldt, and Weill (2015)) and empirical (Oehmke and Zawadowski (2017), Jiang, Ou, and Zhu (2021)) tradition, based on the idea that debt is less liquid than CDS. However, CDS trading on a reference is likely to affect both firms' decision to issue debt and investors' decision to hold debt in general equilibrium.

Empirical contributions on the effect of CDS on reference firm debt tend to show that CDS trading induces firms to issue more debt at a lower rate (Hirtle (2009), Saretto

	Dependent variable:			
	Δ Vol	Δ VaR	Δ Vol	Δ VaR
	(1)	(2)	(3)	(4)
Δ Gini	−0.702	−1.279*		
	(0.930)	(0.680)		
Δ HHI			−0.768***	−0.971***
			(0.201)	(0.255)
MeanOverrating	2.696*		2.480*	
	(1.539)		(1.430)	
Δ HighYield		0.653		−0.093
		(2.714)		(2.693)
Num. obs.	3,102	3,114	3,102	3,114
Quarter FE	Y	Y	Y	Y
Cluster SE	N	N	N	N

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. We winsorize risk metrics at 1% level. Dependent variables are the difference in percentage (for volatility) or percentage points (for value-at-risk) between portfolios with CDS and portfolios without CDS. We change the sign of value-at-risk difference to give the same sign interpretation to volatility and value-at-risk changes. "Δ VaR" corresponds to the 10-day value-at-risk using the filtered historical simulation method. 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. $\Delta Gini$ and ΔHHI are variations in concentration at the investor-quarter level attributable to CDS. $MeanOverrating$ is the mean overrating probability of references sold through speculative strategies at investor-quarter level. $\Delta HighYield$ is the increase in the share of high-yield exposures of speculative strategies at the investor-quarter level attributable to CDS.

Table 6 – Effect of CDS trading strategies on portfolio risk

and Tookes (2013), and Gündüz, Ongena, Tümer-Alkan, and Yu (2017)), and ultimately become riskier (Subrahmanyam, Tang, and Wang (2014)). Our conclusions on reach for yield 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, its dispersion in the financial system will be higher, if there are fixed costs of trading for instance. Hence, CDS-referenced firms will have a more diversified distribution of lenders, which CDS trading will enhance.

Then, CDS and debt holdings are likely to be jointly determined by investors. This 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. We test the relation between reference debt concentration and CDS trading. To do so, we include in our sample the 1,000 firms representing the largest debt holdings by quarter and yet not referencing CDS. Using an appropriate set of controls, we can reasonably measure how lender concentration varies if the firm references a CDS. Our results are housed in Table 7 and lender concentration does not appear to be related to CDS referencing.

	HHI	
	(1)	(2)
CDS Ref	-0.030	-0.243
	(0.020)	(0.179)
Log Gross debt Ref	-0.026^{***}	
	(0.007)	
FR Ref	-0.318^{***}	
	(0.014)	
Num. obs.	17,107	28,409
Rating FE	Y	N
Quarter FE	Y	Y
Ref FE	N	Y
Cluster SE	Ref	Ref
R^2	0.270	0.786

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Reference-level variables have the suffix "Ref". HHI designates $HHI_{jt} = \sum_i \left(\frac{|REAL_{ijt}|}{\Sigma_k |REAL_{kjt}|}\right)^2$. "Log Gross debt Ref" stands for the reference gross debt while "Log Total debt Ref" designates the reference total debt held by investors in the database. "CDS Ref" is a dummy taking value 1 if there is a CDS traded on the reference. In this specification, we extend the data to the top 1,000 largest firms without CDS referenced on their name.

Table 7 – Reference debt concentration (HHI) and CDS trading

The co-determination of debt and CDS positions may also affect our results on reach for yield and portfolio risk. 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 choose to downsize debt positions and substitute for CDS trading. We exploit the time-series variation in CDS trading at the investor level to partially answer this concern. Specifically, we test whether investors out of the CDS market hold a larger share of high-yield debt exposures. Table 8 shows this is not the case.

	Share high-yield debt exposures
CDS trading	0.008
	(0.012)
Observations	3,151
Investor FE	Y
Quarter FE	Y
Clustered SE	Inv
Adjusted R^2	0.877

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. The dependent variable is the share of high-yield debt exposures among total strictly positive debt exposures at the investor-quarter level.

Table 8 – Effect of CDS trading on risk-taking with debt

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, our results emphasize the importance of accounting for CDS when analyzing credit risk distribution.

We make three contributions. First, CDS decrease exposure concentration of both investors and references. Speculators use them as a substitute for debt, while hedgers offset in priority their largest debt exposures. The effect is economically meaningful: HHI decrease by 42% on average for dealers in our sample. Then, we show that speculators use CDS more than debt to reach for yield, both between and within rating classes. These results hold controlling for proxies of relative liquidity. This could be explained by relatively lower margin requirements at lower ratings, or by a relative advantage of CDS opacity. Finally, CDS increase dealers and funds portfolio risk. Both reaching for yield and asset diversification contribute to this increase. Hence, exposure diversification with CDS does not entail return diversification.

A Cleaning CDS positions from DTCC reports

EMIR (648/2012) regulation compels European Union institutions to report their derivative transactions to trade repositories. We use quarter-end credit derivatives reports to DTCC from 2016Q1 to 2019Q4. Abad, naki Aldasoro, Aymanns, D'Errico, Rousová, Hoffmann, Langfield, Neychev, and Roukny (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. Banque de France restriction to French counterparties or French underlyings does not reduce the set of transactions on indexes since they all include at least one French underlying. 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 (CDS, swaption,...), notional, currency, contract 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 keep credit default swaps contracts, hence removing swaptions and more exotic contracts such as spread bets.

B Descriptive statistics

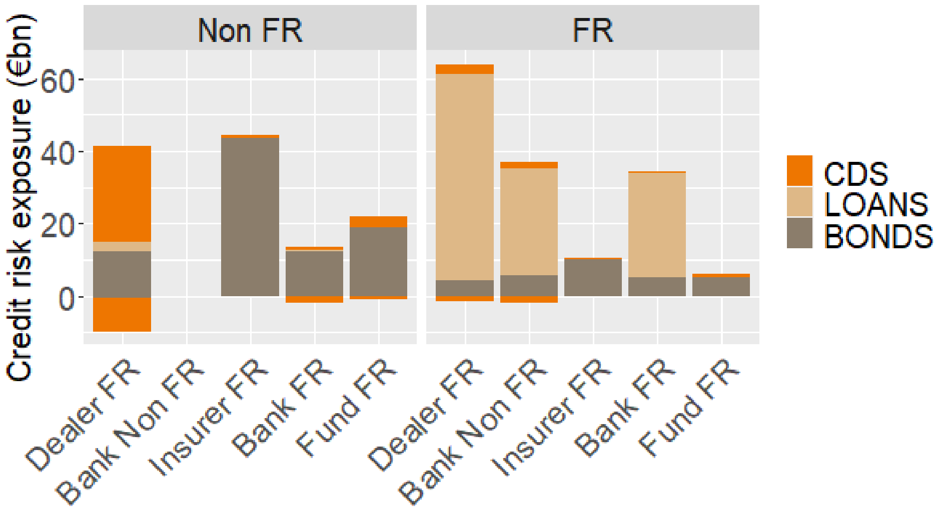


Figure 5 – Debt and CDS exposures to NFC by investment sector and residence of reference as of Q4 2019

Category	#Obs	CDS sell	CDS buy	#CDS sell	#CDS buy	Bonds long	Bonds short	Loans
Bank FR	3	0.88	-1.91	111.38	135.88	14.64	-0.08	27.09
Bank Non FR	32	1.67	-1.43	118.88	60.56	3.75	-0.14	23.84
Dealer FR	3	26.84	-18.17	887.06	621.38	13.83	-1.09	53.90
Fund FR	214	3.46	-2.20	338.56	265.44	25.71	-0.01	0.00
Insurer FR	3	0.77	-0.05	49.88	6.25	56.64	0.00	0.00
NFC FR	69	6.11	-4.15	298.06	193.88	27.79	-0.33	101.94
NFC NFR	910	27.52	-19.61	1207.69	895.62	86.77	-1.00	2.90
All	35991	33.62	-23.75	1505.75	1089.50	114.57	-1.33	104.83
Bond fund	135	2.71	-1.51	275.19	188.00	19.91	0.00	0.00
Mixed fund	54	0.74	-0.68	60.62	69.75	4.75	-0.01	0.00
Other fund	25	0.01	-0.01	2.75	7.69	1.06	0.00	0.00

"#Obs" is the number of observations in the pooled 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 9 – Descriptive statistics

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 ($CDS_{ijt} * Debt_{ijt} \geq 0$) or strictly offset ($CDS_{ijt} * Debt_{ijt} < 0$) each other. 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 $\frac{CDS_{ijt}}{Debt_{ijt}} < -2$. 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 $(+,-)_t$ CDS, 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. If both CDS and debt positions are acquired in a single period, moving from $(+,-)_{t-1}$ or $(0,0)_{t-1}$ to $(-,+)_t$ CDS, then the investor is also 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,[21] and after estimating the pooled distribution of hedging ratios (HR) for each strategy using a gaussian kernel:

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

Case 1: If the CDS position is unwound before the debt position (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 (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 (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.

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*.

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

C.2 Figures and tables

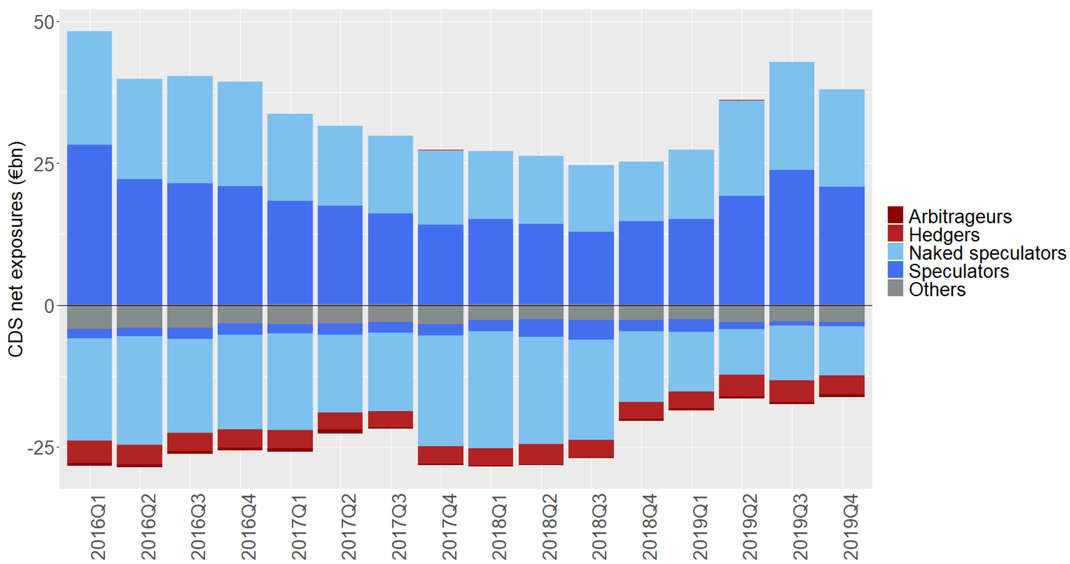


Figure 6 – Aggregate net exposures by strategy over time

Strategy	#Positions	Debt	CDS	HedgingRatio	ResMat		ShareCCP	Persistence	Turnover	
					Debt	CDS			Debt	CDS
Normal	7610	16.29	0.00	0.00	5.67	2.10	0.05	5.38	0.24	0.00
Others	154	0.43	0.13	0.89	5.19	2.17	0.10	9.89	0.00	0.00
Speculators	719	73.10	28.11	1.66	7.15	2.72	0.16	2.79	1.49	0.65
Naked speculators	1504	0.72	20.08	10.81	8.41	2.49	0.13	3.26	0.10	0.43
Hedgers	188	165.76	17.52	0.25	4.97	2.57	0.10	2.93	0.26	0.82
Arbitrageurs	32	15.72	12.76	1.00	3.37	2.60	0.03	3.28	0.20	0.20

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. "Debt" and "CDS" correspond to mean face and notional value in EUR million. "HedRatio" 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. 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 spurious and attributable to our strategy identification method which requires the observation of entry or exit.

Table 10 – Descriptive statistics by strategy

D Methodology to calculate overrating

We follow Boermans and van der Kroft (2020) in deriving an overrating probability for each reference-quarter, with some adjustments that we detail hereafter. We proceed with the following steps.

Step 1: For each reference-quarter, we calculate the probability that given its spread, a reference belongs to the rating class immediately below. We exclude references rated below CCC for which the number of observations is insufficient to derive a distribution. Using Bayes' rule and assuming ratings can only be one notch off, we calculate the probability of being overrated as in Equation 7. We estimate conditional probability distributions using a Gaussian kernel. Equation 7 writes:

$$P(Rating_{below,jt}|Spread_{jt}) = \frac{P(Spread_{jt}|Rating_{below,jt}) * P(Rating_{below,t})}{\Sigma_{k\in\{below,exact,above\}} P(Spread_{jt}|Rating_{k,jt}) * P(Rating_{k,t})}.$$

Step 2: We subtract from $P(Rating_{below,jt}|Spread_{jt})$ the minimum calculated overrating probability by rating notch P^r_{min}, to standardize the metric across ratings.

Step 3: To preserve the monotonicity of the transformation of a spread into an overrating probability by rating class, we assume that for all spreads lower than the minimum's argument by rating class, the overrating probability is null. If we denote by $Spread^r_{min}$ the spread such that $P(Rating_{below,jt}|Spread^r_{min}) = P^r_{min}$, then in each rating notch r, $\forall Spread_{jt} < Spread^r_{min}$, $P(Rating_{below,jt}|Spread_{jt}) = P^r_{min}$. Figure 8 plots the final probability of overrating by notch and spread.

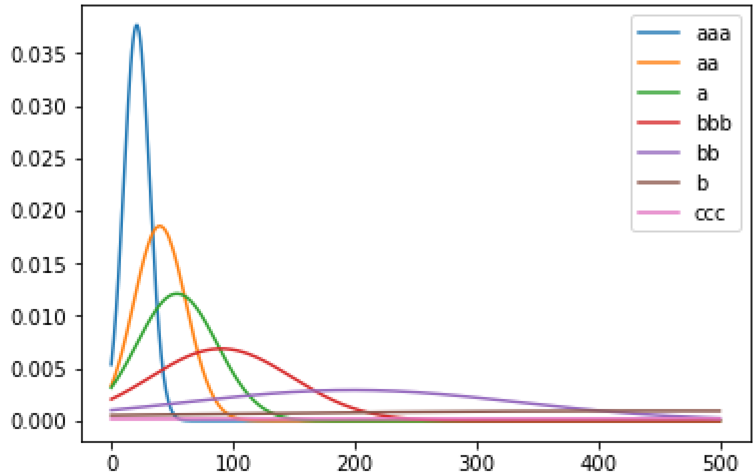


Figure 7 – Spread distributions by rating class

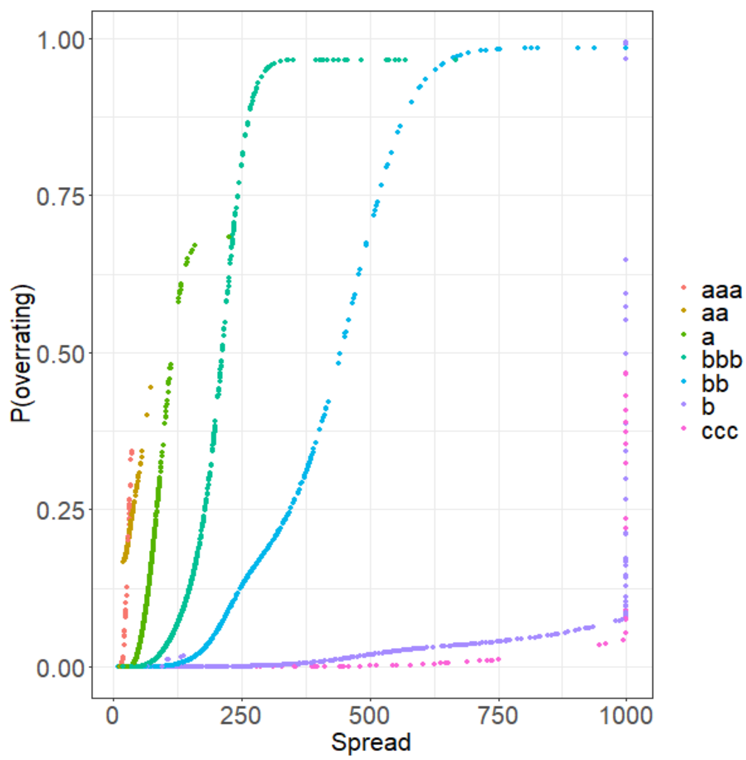


Figure 8 – Probability of overrating by rating notch and spread, censored at 1,000bps

E Remaining tables and figures

	P(Hedger)					
	(1)	(2)	(3)	(4)	(5)	(6)
Share debt exposure	39.03***	18.25***	43.73***	72.78***	39.25**	17.32***
	(10.00)	(4.26)	(9.61)	(15.83)	(17.47)	(2.85)
Log Debt	0.43***	0.52***	0.46***	0.81***	0.21***	0.47***
	(0.04)	(0.03)	(0.03)	(0.05)	(0.06)	(0.02)
Log Total exp Inv		−0.01				−0.02
		(0.04)				(0.03)
FR Inv		0.78***				0.64***
		(0.09)				(0.08)
Bank						−0.96***
						(0.36)
Dealer		0.25***				−0.77**
		(0.07)				(0.37)
Fund		−2.15***				−2.98***
		(0.17)				(0.32)
Insurer		−2.99***				−3.74***
		(0.17)				(0.37)
CDS liquidity Ref			1.08***			1.02***
			(0.10)			(0.08)
Log Gross debt Ref			−0.04***			−0.05***
			(0.01)			(0.02)
IG Ref			−0.30***			−0.35***
			(0.09)			(0.06)
FR Ref			−0.07			−0.13**
			(0.08)			(0.06)
Num. obs.	13522	37005	32117	5950	5792	80261
Ref x Quarter FE	1679	1679		1101	578	
Inv x Quarter FE	425		421	267	291	
Cluster SE	Inv x Q	Ref x Q	Inv x Q	Inv x Q	Inv x Q	Inv x Q
IBP correction	Y	N	N	Y	Y	N

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Logistic regressions on subsample of long debt owners with over €1mn holdings. Sector effects are with respect to banks. "Share debt exposure" designates $\frac{Debt_{ijt}}{TotExp_{it}}$. Reference-level (resp. investor-level) variables have the suffix "Ref" (resp. "Inv"). "CDS liquidity Ref" is a dummy taking value 1 for the top 1,000 most liquid references as reported by DTCC. Specification (4) and (5) restrict respectively to non-French and French references, acknowledging that the concentration of French investors exposures to French references may be biased upwards. Specification (6) does not include fixed effects to abstract from the incidental parameter bias. In specifications (1), (4) and (5), coefficients are corrected from the incidental parameter bias using the methodology developed by Fernández-Val and Weidner (2016).

Table 11 – Robustness on concentration: probability to hedge

	P(Speculator)					
	(1)	(2)	(3)	(4)	(5)	(6)
Share debt exposure	-27.00^{***}	-14.53^{**}	-29.48^{***}	-19.72^{*}	-47.61^{***}	-16.91^{***}
	(7.59)	(5.65)	(6.84)	(10.20)	(17.56)	(4.54)
Log Debt	-0.01	-0.04^{***}	0.03	0.04	0.07	0.09^{***}
	(0.02)	(0.01)	(0.03)	(0.04)	(0.05)	(0.01)
Log Total exp Inv		0.40^{***}				0.29^{***}
		(0.02)				(0.02)
FR Inv		-0.54^{***}				-0.64^{***}
		(0.06)				(0.06)
Bank						-5.30^{***}
						(0.27)
Dealer		1.95^{***}				-2.69^{***}
		(0.05)				(0.28)
Fund		0.10				-5.51^{***}
		(0.11)				(0.25)
Insurer		-0.52^{***}				-5.96^{***}
		(0.06)				(0.27)
Log Gross debt Ref			0.13^{***}			0.08^{***}
			(0.02)			(0.01)
Top 1000 CDS Ref			1.56^{***}			2.11^{***}
			(0.07)			(0.06)
IG Ref			0.05			0.10^{**}
			(0.06)			(0.04)
FR Ref			0.58^{***}			0.33^{***}
			(0.06)			(0.04)
Num. obs.	28970	61866	38626	17419	8630	74175
Inv x Quarter FE	667		655	405	469	
Ref x Quarter FE	3929	4004		3180	700	
Cluster SE	Inv x Q	Inv x Q	Ref x Q	Inv x Q	Inv x Q	Inv x Q
IBP correction	Y	N	N	Y	Y	N

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Logistic regressions on subsample of long debt owners with over €1 mn holdings. Sector effects are with respect to banks. "Share debt exposure" designates $\frac{Debt_{ijt}}{TotExp_{it}}$. Reference-level (resp. investor-level) variables have the suffix "Ref" (resp. "Inv"). "CDS liquidity Ref" is a dummy taking value 1 for the top 1,000 most liquid references as reported by DTCC. Specification (4) and (5) restrict respectively to non-French and French references, acknowledging that the concentration of French investors exposures to French references may be biased upwards. Specification (6) does not include fixed effects to abstract from the incidental parameter bias. In specifications (1) (4) and (5), coefficients are corrected from the incidental parameter bias using the methodology developed by Fernández-Val and Weidner (2016).

Table 12 – Robustness on concentration: probability to speculate

	CDS Sell vs Bond Spread	CDS Sell Spread	CDS Buy Spread
	(1)	(2)	(3)
Bank	17.78^{***}	-13.57^{***}	-18.50^{***}
	(3.14)	(3.19)	(5.19)
Dealer	42.39^{***}	4.30^{*}	45.60^{***}
	(6.38)	(2.39)	(16.19)
Fund	36.78^{***}	21.18^{*}	-4.40
	(9.67)	(11.72)	(5.02)
Insurer	-2.34^{**}	-15.52^{***}	2.41
	(0.91)	(1.40)	(6.04)
Num. obs.	927	975	833
Cluster SE	Q	Q	Q

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. The dependent variables are the following: (1) notional-weighted spread of CDS sold minus weighted bond spreads, at investor x quarter level; (2) notional-weighted spread of CDS sold minus mean spread in high-yield and investment-grade categories of CDS in the dataset, at investor x quarter level; (3) identical to previous with CDS purchased.

Table 13 – Replication of reach for yield results from Jiang, Ou, and Zhu (2021)

	Normalized spread			
	Benchmark (1)	FR-FR (2)	FR-NFR (3)	NFR-FR (4)
Long Speculators	0.17***	−0.03	0.24***	0.08***
	(0.02)	(0.02)	(0.02)	(0.03)
Short Speculators	0.14***	0.02	0.18***	0.06
	(0.01)	(0.03)	(0.02)	(0.05)
Short Hedger	0.09***	−0.05	0.20***	−0.02
	(0.02)	(0.03)	(0.04)	(0.05)
Other CDS	0.08***	−0.16**	0.16***	−0.18***
	(0.03)	(0.06)	(0.03)	(0.05)
Log Gross debt Ref	0.05***	0.11***	0.04***	0.14***
	(0.00)	(0.00)	(0.00)	(0.01)
CDS liquidity Ref	−0.19***	0.09***	−0.24***	0.09*
	(0.02)	(0.02)	(0.02)	(0.05)
Num. obs.	90572	90387	73647	73499
Adjusted R^2	0.18	0.36	0.15	0.33
Inv x Quarter FE	Y	Y	Y	Y
Ref Rating FE	Y	Y	Y	Y
Cluster SE	Inv x Q	Inv x Q	Inv x Q	Inv x Q
Model	Panel	Panel	Panel	Panel

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. "Normalized spread" is the difference between the spread and mean spread by rating, normalized by the spread standard deviation by rating. Column (1) includes all speculators. Column (2) includes French exposures to French references, column (3) French exposures to non-French references, and column (4) non-French exposures to French references. Reference-level variables have the suffix "Ref". "Long speculator" designates strategies with (weakly) positive bond and (strictly) positive CDS exposures, and symmetrically for "Short speculator". "CDS liquidity Ref" is a dummy taking value 1 for the top 1,000 most liquid references as reported by DTCC.

Table 14 – Regulatory arbitrage by trading strategy and country

	Dependent variable:			
	Count		Value	
	Δ Vol	Δ VaR	Δ Vol	Δ VaR
	(1)	(2)	(3)	(4)
Bank:CDS Intensity	-0.829	0.011	1.003	0.317
	(3.669)	(0.451)	(4.484)	(0.707)
Dealer:CDS Intensity	3.431^{**}	0.302^{***}	-0.522	0.071
	(1.447)	(0.095)	(0.718)	(0.133)
Fund:CDS Intensity	2.856^{***}	0.549^{***}	2.330^{**}	0.513^{***}
	(1.076)	(0.207)	(1.026)	(0.163)
Insurer:CDS Intensity	-5.243	-0.735^{**}	-7.443^{*}	-2.912^{***}
	(3.365)	(0.313)	(4.249)	(1.089)
Num. obs.	3,129	3,108	3,129	3,108
Adjusted R^2	0.056	0.281	0.056	0.296
Quarter FE	Y	Y	Y	Y
Investor FE	Y	Y	Y	Y
Cluster SE	Inv	Inv	Inv	Inv

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. We winsorize risk metrics at 1% level. In columns (2) and (3), CDS Intensity stands as the ratio of the number of CDS positions to the total number of positions at the investor-quarter level. In columns (4) and (5), it is measured as a ratio of absolute credit risk exposures. Dependent variables are the difference in percentage (for volatility) or percentage points (for value-at-risk) between portfolios with CDS and portfolios without CDS. We change the sign of value-at-risk difference to give the same sign interpretation to volatility and value-at-risk changes. "Δ VaR" corresponds to the 10-day value-at-risk using the filtered historical simulation method. 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.

Table 15 – Effect of CDS on portfolio risk by sector with investor fixed effects

	Dependent variable:			
	Δ Vol	Δ VaR	Δ Vol	Δ VaR
	(1)	(2)	(3)	(4)
Intercept	-0.028^{***}	0.011	-0.020^{***}	0.026^{***}
	(0.007)	(0.009)	(0.007)	(0.008)
LongSpeculators	0.075^{***}	0.015^{*}	-0.054	-0.037
	(0.022)	(0.008)	(0.062)	(0.024)
ShortSpeculators	0.980^{***}	0.409^{***}	1.086^{***}	0.456^{***}
	(0.132)	(0.045)	(0.208)	(0.082)
ShortHedger	-1.188^{**}	-0.552^{***}	-0.908^{*}	-0.564^{**}
	(0.564)	(0.202)	(0.484)	(0.263)
OtherCDS	0.780	0.689^{*}	2.286	1.409
	(0.892)	(0.399)	(1.585)	(0.860)
Num. obs.	2,937	2,932	2,937	2,932
Quarter FE	Y	Y	Y	Y
Investor FE	N	N	Y	Y
Cluster SE	Inv	Inv	Inv	Inv
Adjusted R^2	0.476	0.213	0.606	0.302

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. We winsorize risk metrics at 1% level. Dependent variables are the difference in percentage (for volatility) or percentage points (for value-at-risk) between portfolios with CDS and portfolios without CDS. We change the sign of value-at-risk difference to give the same sign interpretation to volatility and value-at-risk changes. "Δ VaR" corresponds to the 10-day value-at-risk using the filtered historical simulation method. 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. Strategies are continuous variables equal to the share of absolute notional CDS value of each strategy by investor-quarter. We remove observations when the share of a strategy is in the top 1% of that strategy's share distribution.

Table 16 – Effect of CDS trading strategies on portfolio risk

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