Bank Use of Sovereign CDS in the Eurozone Crisis: Hedging and Risk Incentives

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February 18, 2022

Abstract

Using a comprehensive dataset from German banks, we document the usage of sovereign credit default swaps (CDS) during the European sovereign debt crisis of 2008-2013. Banks used the sovereign CDS market to *extend*, rather than hedge, their long exposures to sovereign risk during this period. Lower loan exposure to sovereign risk is associated with greater protection selling in CDS, the effect being weaker when sovereign risk is high. Bank and country risk variables are mostly not associated with protection selling. The findings are driven by the actions of a few non-dealer banks which sold CDS protection aggressively at the onset of the crisis, but started covering their positions at its height while simultaneously shifting their assets towards sovereign bonds and loans. Our findings underscore the importance of accounting for derivatives exposure in building a complete picture and understanding fully the economic drivers of the bank-sovereign nexus of risk.

Keywords: Credit derivatives, Credit default swaps, Sovereign credit risk, Eurozone, Sovereign debt crisis, Depository Trust and Clearing Corporation (DTCC).

JEL Codes: G01, G15, G21, H63.

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1 Introduction

Nearly two decades after the creation of credit derivatives and following two major western financial crises, viz., the global financial crisis of 2007-08 and the Eurozone debt crisis of 2011-12, there is still little consensus on whether or not these instruments are beneficial for the stability of the financial sector. In the midst of the recent Eurozone debt crisis, European Union (EU) regulators undertook significant steps[1] to curtail the use of ordinary single-name credit default swaps (CDS) referencing EU sovereign entities in the apparent belief that whatever their benefits for risk management, these instruments had the potential to destabilize the credit risk of sovereigns and even threaten the existence of the euro itself. Yet this action was taken against a backdrop of almost no public information on or analysis of how sovereign credit default swaps (SovCDS) were being used at the time.

This paper begins to fill in this gap by providing a detailed examination of the actions of an important subset of actors during the Eurozone crisis. We analyze the evolution of the SovCDS positions of the entire German banking sector from January 2008 to June 2013. Our data allow us to see each German bank's individual CDS position for each country. This enables us to offer a detailed look at how individual banks managed their CDS positions and sovereign risk during the Eurozone debt crisis. In doing so, we provide some of the first direct evidence on how bank and country variables affect derivatives usage under conditions of stress. How and why were these banks using SovCDS? Did they want to extend their sovereign risk exposure or to hedge it, and how did this usage interact with their primary exposure to sovereign risk during this episode? Finally, did SovCDS usage by banks strengthen or weaken the bank-sovereign nexus of risk?

To recall the background, Figures 1 and 2 illustrate the evolution of sovereign and

[1] After the German Federal Financial Supervisory Authority (BaFin) prohibited naked buying of credit default swaps based on euro-denominated government bonds on May 19, 2010, the European Parliament banned such naked CDS Europe-wide on December 1, 2011. The relevant regulation took effect on November 1, 2012, and remains in place at the time of writing. The impact of the ESMA ban is analyzed in Section 4.3.

bank credit risk during our sample period. Our sample begins shortly after the onset of the U.S. subprime crisis and shortly before the collapse of Lehman brothers (September 15, 2008). Figure 1 shows cross-country average sovereign CDS spreads (in basis points per year, for a 5-year contract) for Germany, for the most troubled EU countries[2], and for the other countries in our sample. Also shown is the iTraxx SovX index, which is an average of all western European sovereign CDS spreads, created in September 2009.

[Figure (1) here]

The figure shows the dates of two key peaks of stress in the sample, corresponding to developments in Greece and the most salient event ending the crisis, namely the announcement of effectively unlimited intervention – "whatever it takes" – by Mario Draghi, the President of the European Central Bank (ECB).

Figure 2 depicts the movements of the average CDS spread of German banks in our sample. The average spread follows the pattern of the German sovereign spread over the sample. However, there is also considerable heterogeneity across banks. The figure shows the overall stronger credit (lower spread) for the three large global banks designated as dealers, as well as the weaker non-dealers. The latter group includes one bank, which did in fact need to be bailed out by the German government during 2008. The data in our study thus display unprecedented variation in credit risk in time-series as well as cross-sectionally, both for the entities referenced in the contracts and for the actors who are trading them.

[Figure (2) here]

Since their widespread adoption by banks in the early 2000s, CDS have been primarily viewed and analyzed in the literature as a tool for credit risk transfer by loan originators. A large body of theoretical work (including Duffee and Zhou (2001), Morrison (2005), Instefjord (2005), Allen and Carletti (2006), Duffie (2008), Bolton and Oehmke (2011),

[2]We use the abbreviation GIIPS - for Greece, Ireland, Italy, Portugal, and Spain - throughout to refer to this subset of countries.

Parlour and Winton (2013), and Merton, Billio, Getmansky, Gray, Lo, and Pelizzon (2013)) has addressed the potential effects of this type of risk transfer via CDS on bank risk, systemic risk, loan outcome and credit provision. A basic implication of this work is that, if it is optimal to hedge at all, the amount of hedging should be expected to scale with the quantity and degree of risk exposure to the underlying reference asset. Recent theoretical evaluation in Sambalaibat (2021) implies that the introduction of CDS increases the liquidity and price of bonds by expanding the feasible trade set and attracting investors into the credit market.

Empirical evidence on banks' use of corporate credit derivatives reports indicates different scales of hedging by banks. Gündüz, Ongena, Tümer-Alkan, and Yu (2017) document that extant credit relationships of German banks with riskier corporate borrowers increase banks' CDS trading and hedging of these exposures, whereas Gündüz (2018) documents hedging by banks of counterparty risk with other financial firms using CDS. However, Minton, Stulz, and Williamson (2009) study U.S. banks' loan and CDS positions during 1999-2005 and find that few banks transfer any loan risk at all, and that the aggregate amount of such transfers is negligible. Recently, Czech (2021) shows that large financial institutions primarily sell corporate CDS for expanding their credit exposure rather than hedging it, and Jager and Zadow (2021) provides evidence (as well as theory) that improvement in the CDS contract, specifically the introduction of centralized clearing, drives investor demand away from corporate bonds towards CDS.

To our knowledge, no theoretical models or empirical studies have specifically addressed the issue of credit risk transfer where the underlying borrower is a sovereign rather than a corporate entity. In this context, our sample is especially interesting given the large surge in the quantity and riskiness of sovereign debt during the European crisis. Moreover, as documented by Acharya and Steffen (2015), Becker and Ivashina (2018), and Crosignani (2021), banks absorbed an increasingly large fraction of this debt as the crisis went on. On the one hand, if economic hedging with sovereign CDS were ever to be desirable, this would seem to be the most likely setting. On the other hand, to the extent that hedging or risk transfer of corporate loans is motivated by the desire to free up regulatory capital for balance sheet lending capacity, this does not apply to sovereign exposure, which carries a zero capital charge for banks in our setting.

In this context, the first-order finding of this paper is remarkable: German banks actually used CDS referencing EU countries to extend rather than hedge their exposure to sovereign credit risk throughout the crisis. The selling of credit protection was widespread across banks and countries, and its scale was economically large, particularly for smaller banks. We observe that banks hedged long sovereign bond positions by purchasing CDS protection in only 10.5% of the cases in which such bond positions were held, whereas we see the opposite – banks selling protection and simultaneously holding long bond positions – four times as often. Not only were the incentives to hedge not present, it appears at first glance as if banks were operating in reverse.

In seeking to understand the incentives to sell SovCDS, we are naturally led to the literature on risk-shifting and moral hazard (or "regulatory arbitrage") by banks. Here, theoretical considerations (Jensen and Meckling (1976), Bhattacharya and Thakor (1993), Farhi and Tirole (2012), Acharya, Mehran, and Thakor (2016) and Crosignani (2021)) suggest that incentives to extend risk exposure could be the greatest for banks with weakest capital positions or highest levels of risk, and moreover, that these banks would be expected to increase exposure to the riskiest entities.

Indeed, the recent empirical literature on the interaction of government financing and the banking system highlights distortionary mechanisms operating during the crisis. Acharya and Steffen (2015) document increased risk taking, particularly by undercapitalized Eurozone banks on zero-risk weight sovereign bonds. Buch, Koetter, and Ohls (2016) also show that less capitalized German banks held more sovereign bonds during this period. The two-way feedback loop between banks and sovereigns (Acharya, Drechsler, and Schnabl (2014)) could create a particularly strong risk-enhancing effect, prompting banks to write SovCDS.

Here, several of our negative findings are notable. Overall, we do not find evidence that bank risk variables are associated with protection selling. Also, the marginal effect of the level of sovereign risk is to decrease protection selling, not increase it. And there is no significant interaction between bank risk and sovereign risk. These findings suggest that risk-shifting, in its traditional incarnation, is not driving the use of sovereign CDS. By contrast, we do find some evidence that deposit inflows to large banks during the crisis (a classic flight to safety) were associated with those banks selling risky sovereign protection. A large body of literature shows that when deposit inflows are insensitive to bank fundamentals due to deposit insurance or implicit guarantees such as "too-big-to-fail", easy liquidity can lead to excessive risk taking (e.g., Myers and Rajan (1998), Calomiris and Jaremski (2016)).

Our strongest finding is a significant negative association between SovCDS trading and the ratio of risk-weighted assets (RWA) to bank loans. However, we do not view this as a bank risk effect. Rather, we argue that since our specifications include explicit controls for bank risk (the bank's own CDS spread) and capital strength (bank's Tier 1 capital ratio), the risk-weighted asset ratio should be viewed as a proxy for a bank's total primary exposure (via loans and bonds) to sovereign risk. Holding bank risk constant, a bank with lower RWA is one that has a relatively higher level of risky sovereign loan exposure in relative terms (which nevertheless carries a zero risk weight), whereas a bank with higher RWA has greater commercial loan exposure (which carries a higher risk weight).

Under this interpretation, our results point to a *portfolio substitution* effect, whereby banks with less primary sovereign exposure are more likely to take on sovereign credit risk by selling CDS protection. This is consistent with an overall asset allocation shift to sovereign risk by the banking sector, but with some banks choosing to implement this position via derivatives instead of directly through sovereign bond holdings. These results are driven by the activity of relatively smaller non-dealer banks. Dealers, by contrast, sell less protection overall and do not exhibit the same substitution effects. In fact, among the non-dealers, most of the sovereign CDS risk is borne by just three institutions, which made extremely aggressive bets at the start of the crisis and covered their positions at its height.

Correspondingly, we find that GIIPS countries' credit risk significantly flows through into the credit risk of these non-dealer banks, and these banks' SovCDS underwriting also contributes to a material widening of their own CDS.[3]

These results have important policy implications for bank regulation and management of bank-sovereign risk nexus. First, we provide new evidence on factors that are, and are not, responsible for sovereign risk-taking by banks using the credit derivatives markets; in particular, and consistent with the recent evidence for corporate CDS, SovCDS appear to be used as substitutes for sovereign exposure via direct holdings of bonds and loans. This suggests that a full understanding of the bank-sovereign risk dynamic in the crisis requires factoring SovCDS into the picture rather than just relying on holdings of bonds and loans. Second, our specific result that smaller non-dealer banks in Germany are at the center of such substitution activity implies that regulatory stress tests which focus on larger banks and dealers might miss out on the potential "hot spots" of bank-sovereign nexus. Since one of these non-dealer banks was in fact bailed out by the German government, the implication is that assessing the true exposure of taxpayers to bank risks via the sovereign risk channel requires paying attention also to the credit derivatives activity of smaller banks, and more generally, non-banks.

2 Data and Descriptive Statistics

2.1 Sources of Data

Our data on credit derivatives use are provided by the Depository Trust and Clearing Corporation (DTCC), more specifically its proprietary position-level data on German banks' sovereign CDS positions. With its Trade Information Warehouse (TIW), DTCC captures around 95% of all single-name CDS transactions worldwide and builds weekly snapshots

[3]Although sovereign bonds and derivatives on EU countries have the same zero-risk weight privilege and are therefore treated equally for regulatory capital purposes, cash bond positions require financing (via the repo market), whereas CDS do not. In addition, CDS positions remain off balance sheet, which some banks might prefer. Substitution motives also vary independently of bank characteristics with the relative price of credit risk in the bond and CDS markets for a given country. We document that this difference (the "basis") is also a significant determinant of banks' protection selling.

of bought and sold positions on each reference entity for each financial institution.[4] The inventories that are built by DTCC include all confirmed new trades, assignments, and terminations on contracts referencing each sovereign entity. Within the observation period of January 2008 to August 2013,[5] our sample comprises all 16 banks active in the CDS market, and is therefore inclined towards the larger players in the German banking system.[6] Ten of these 16 banks are among the 60 largest European banks by asset size as at end-2013. Moreover, six of them would have ranked among the ten largest US banks by asset size, according to 2013 figures. For each sovereign-bank pair, and at each date, we compile the net CDS position held by the bank in any contract referencing any arm of the sovereign entity, where the netting aggregates contracts of possibly differing maturities, restructuring clauses, currency denomination, and other protocols.

Banks' regulatory ratios are retrieved from the Deutsche Bundesbank's Prudential Database (BAKIS). Other bank-specific information concerning e.g. loans and advances to non-bank institutions and overnight deposits owed to non-German banks are retrieved from the Bundesbank's monthly balance sheet statistics (BISTA). Individual sovereign positions of loans and bondholdings of German banks are taken from the Bundesbank's External Position of Banks Database (AUSTA). In addition, we use Eurostat's consolidated government gross debt figures for each country.

We collect daily composite CDS prices of sovereigns and banks as well as the iTraxx SovX index for Western Europe from the Markit database. For each sovereign nation on each date, we use the CDS fee on the 5-year maturity contract with a CR restructuring clause denominated in US dollars as our reference price for credit protection. Other

[4]See DTCC (2009) on global coverage. Note that our regulatory access to DTCC positions enables us to see each bank's position on each sovereign, which is more granular than in the studies with website access to DTCC aggregate positions only, i.e. Oehmke and Zawadowski (2017), or Augustin, Sokolovski, Subrahmanyam, and Tomio (2021). In the appendix, Table A1 presents a summary of the literature that makes use of DTCC positions and transaction data so far.

[5]The DTCC actively began building its Trade Information Warehouse (TIW) database in 2008, and frontloaded all prior transactions after their inception date. For our purposes, then, the earliest possible starting point for a reliable time series was January 2008.

[6]As of the end of 2013, there were 1,726 banks in Germany that reported income and loss statements to the Bundesbank, of which 62% were credit cooperatives and 24% were savings banks. These are smaller banks which mostly target local deposit and loan businesses, and are not typically active in OTC derivatives markets.

variables, such as the EUR/USD exchange rate and the VSTOXX volatility index, are from Bloomberg. Finally, we make use of Thomson Reuters Government Benchmark 5-year maturity Bid Yields in order to construct the bond-CDS basis.

2.2 Descriptive Characteristics of German Banks throughout the Crisis

Table 1 presents the statistics for the 16 German banks in our sample. The DTCC classifies any institution "which is in the business of making markets or dealing in credit derivative products" as a CDS "dealer",[7] and three of our sample banks fall into this category (Deutsche Bank AG, Commerzbank AG, and Unicredit). Our analysis includes a separate examination of dealer and non-dealer positions as they play different roles in the CDS market.

[Table (1) here]

German banks recorded an average weekly CDS price of 162 bps during the period 2008-2013. The 13 non-dealers had a high variation (128 bps) of riskiness, and their average CDS spread (169 bps) was higher than the average of our three dealers in the sample (138 bps). In order to harmonize the CDS time series with monthly/quarterly financial information, we chose to work with monthly log differences of CDS prices. On average, the monthly changes were positive across our sample period as credit risk among EU nations deteriorated.

Total loans and advances to non-banks are used as our main gauge of bank size. We refer to this statistic throughout as non-bank assets, or NBA. By this measure, dealers are more than three times larger than non-dealers on average.

Regulatory capital plays an important role in our analysis. We define two relevant metrics based on each bank's reported "risk-weighted assets". This is a standard regulatory calculation which applies fixed risk weights to each category of bank asset (with

[7]See DTCC (2009). In addition, the DTCC automatically classifies the G14 dealers as "dealer banks": Bank of America Merrill Lynch, Barclays Capital, BNP Paribas, Citi, Credit Suisse, Deutsche Bank, Goldman Sachs, HSBC, JP Morgan, Morgan Stanley, RBS, Société Générale, UBS, and Wells Fargo Bank.

a higher weighting denoting an assumed greater risk). The RWA ratio is calculated as risk-weighted assets divided by NBA, and the Tier 1 ratio is calculated as the quarterly core capital (common book equity plus retained earnings) divided by risk-weighted assets. Unconditionally, dealers and non-dealers do not differ much on either dimension.

To gauge flight-to-quality effects, we also consider deposit flows of German banks. To this end, we focus on flows to/from non-German banks (net flows from (domestic and foreign) households and other non-bank entities are small and fairly stable over the sample period). The last two rows in Table 1 show that this source of funds is, on average, much larger in the case of dealers than for non-dealers, both in absolute terms and as a percentage of assets.

2.3 The DTCC Dataset on Sovereign CDS Holdings

Our dataset covers the CDS positions of 16 German banks referencing all countries over the observation period. In an attempt to utilize the sovereign entities whose CDS are most actively traded, we identified the 20 European countries whose banks are included in the stress tests conducted by the European Banking Authority (EBA), starting in 2009. Some of our analysis separately considers the sovereign risk of the GIIPS countries, namely Greece, Ireland, Italy, Portugal, and Spain, which proved ex post to be the most at risk of default during the European debt crisis.[8]

The key variable of interest is the sovereign CDS holdings of the banks in our sample. We use the term "DTCC" for this position-level variable in Table 2 and in our subsequent analysis. This weekly snapshot of a bank's bought and sold CDS position on a sovereign can be used as a net value after subtracting the sold position from what is bought. The negative net value (-84 EUR million) in the first row of statistics in Panel A of Table 2 indicate that the German banks are net sellers of sovereign CDS within the 2008-13 period. This finding is noteworthy because it immediately rules out a primary hypothesis

[8]The remaining 15 non-GIIPS countries in our sample are Austria, Belgium, Cyprus, Denmark, Finland, France, Germany, Hungary, Malta, the Netherlands, Norway, Poland, Slovenia, Sweden and the UK.

about the usage of credit derivatives, namely that they are used to hedge banks' loan and bond exposure to sovereign risk (The aggregate positions are discussed in the next section).

[Table (2) here]

Our empirical analysis attempts to shed light on the factors driving banks' CDS selling. We use as our primary measure the monthly difference of the net CDS position, which reveals the trading activity during one month. Its average value is near zero (-0.69 EUR million), though with a standard deviation of 41 EUR million. The highly fluctuating nature of dealer banks' trading activity can be observed from the standard deviation of 67 EUR million, which well exceeds that of the 13 non-dealers (33 EUR million). In order to ensure the robustness of the trading activity variable, we alternatively scaled the net CDS position with (i) non-bank assets, which is a bank-specific variable, and (ii) total sovereign debt from Eurostat, which is a country-specific variable.

Our econometric analysis will distinguish between position changes that are zero and non-zero. Table 2 additionally provides the statistics of the weekly positions excluding zero values. The average weekly net CDS position for all banks jumps to -177 EUR million when zero positions are factored out. Moreover, the standard deviation of the 13 non-dealers (545 EUR million) now exceeds that of the three dealers (440 EUR million), which shows that dropping the inactive bank-country positions results in a remaining set of observations with high volumes for the non-dealers.

In addition, Panel B in Table 2 shows the value for sovereign CDS prices averaged over all countries and weeks. The average sovereign CDS price is 210 bps with a high variation of 619 bps, which is mainly attributable to the sovereign credit risk problems of several stressed European economies. Analogously to the CDS prices of banks, we make use of monthly log CDS spread differences of sovereigns in our analysis.

Finally, a key variable for assessing bank exposure is the sovereign bond holdings of banks in each individual country, which are available on a monthly basis. This comprises both positions held for trading purposes (the "trading book") and those held to maturity (the "loan book"). As expected, German banks were very long on sovereign risk in these primary securities. Of all the bank-country-month observations in our sample, 71% were long positions while short positions accounted for only 5% of these observations. Averaging across all observations, excluding those for German government bonds, produces a position size of 231 EUR million in bond value. Multiplying by 19 (the number of nations in the sample, excluding Germany) produces an average bank-month exposure to sovereign debt of 4.4 EUR billion. Multiplying by 16 (the number of banks in the sample) gives an average exposure of the banking system of 70 EUR billion during the sample period.

2.4 Time Series Properties of Bank CDS Positions

As already described, the data reveal that German banks were net protection sellers on Eurozone sovereign entities during the debt crisis. Combining our CDS data with sovereign bond positions holdings confirms that the CDS exposure reinforced the primary exposure to sovereign risk. Of the 71% of sample observations with long sovereign bond positions, the net CDS position is negative in 42% of these cases and is positive in only 10.5% of such observations. We will now describe the evolution of the banks' aggregate positions over the sample period.

Figure 3A depicts, on the left axis, the total net SovCDS positions of all 16 banks. German banks were already net sellers in early 2008; however, this position became amplified and reached its peak in early 2010. At approximately 40 EUR billion, the total exposure to sovereign risk was economically large. By comparison, the Tier 1 capital of our 16 banks totalled approximately 200 EUR billion at the time. The second axis on the right gives the aggregate positions scaled by each bank's assets (NBA). In these units, the total net protection selling position reached an extremely large 44% in January 2010.[9] Over the course of the sample, banks closed their protection selling position by almost

[9]This calculation sums the positions, each of which has been scaled by NBA, across our 16 banks. Thus the maximal exposure represents $2.75 = 44/16\%$ of each bank's own assets.

half, as of mid-2013. Even these diminished positions constituted a substantial fraction of the total net outstanding positions in these reference entities. Table 3 shows the net position share of our banks by country compared to the global net position outstanding in that country at the end of our sample period.

[Table (3) here]

A closer look at the positions reveals that three of the bank positions account for almost three-quarters of overall protection selling positions in the market during peak times in 2010, reaching a value of over 30 EUR billion (Figure 3B). This value is reached when the three largest sell positions are aggregated on each date separately. By contrast, the three largest protection purchase positions cumulatively account for only a very small positive amount.

Figure 3C further reveals that the three banks that are responsible for the high protection selling position are non-dealers: the top three protection selling positions in Figure 3B are revealed to be almost fully attributable to three specific non-dealers in Figure 3C. The three dealers in our sample are likewise net protection sellers; however, the three main protection selling non-dealers have an aggregate magnitude amounting to over 30 EUR billion in 2010, far exceeding that of the dealers. The magnitude of the "big three" non-dealers' short position reaches 30 EUR billion at the start of 2010. By comparison, their total assets (NBA) at the end of 2009 amounted to 326 EUR billion, and their total Tier 1 capital stood at 28 EUR billion.

Finally, around two-fifths of the protection selling exposure of these three non-dealers is towards GIIPS countries, which exceed 12 EUR billion of protection sold (Figure 3D). We observe here that dealers also have a protection selling position on GIIPS countries that reach 7 EUR billion in early 2011. By contrast, the position-taking behaviour of the remaining non-dealers is negligible.

[Figure (3) here]

Explaining the time-series and cross-sectional patterns of bank protection selling is the goal of the econometric tests described in the next section.

3 Empirical Methodology

To understand the determinants of sovereign risk-taking, we examine the monthly changes of DTCC positions of a bank on a sovereign, which contain all CDS trading activity within the month. This will be our main dependant variable of interest (*dif_dtcc*). We additionally use bank-specific or sovereign-specific standardized CDS positions by dividing the monthly changes by the level of non-bank assets (*dif_dtcc_nba*) or by the level of sovereign debt (*dif_dtcc_debt*), respectively. This scaling enables us to control for bank-level and sovereign-level size effects separately.

3.1 Hypothesis Development

As our initial look at the data has revealed, the salient feature of bank CDS positions to be explained is the aggressive protection selling at the onset of the crisis, followed by the attenuation of these positions over the sample period. Guided by the literature on bank risk-taking and derivative usage, we look for explanatory variables that can account for this pattern. While the overall U-shaped pattern in bank exposures may appear to be explained by a number of macroeconomic variables, our study is able to utilize both cross-bank and cross-sovereign variation to discriminate against a number of hypotheses. We will now review some of these hypotheses, and explain our selection of independent variables.

First, derivatives usage is most naturally gauged in the context of primary market exposure to the same risks. Moreover, any consideration of hedging or risk management would suggest that the degree of riskiness of those exposures would increase the incentives to buy protection.

On the other hand, risk-shifting motivations might suggest greater protection selling on riskier entities, or a "reaching for yield" effect. Theoretical arguments also suggest that bank weakness (low capital) or risk could enhance risk-shifting motivations, and that the incentives of weaker banks to write protection would be the strongest for risky reference entities. Risk-shifting may also be enhanced through deposit inflows, as discussed in the introduction.

It is worth emphasizing, however, that the intuitions and arguments behind these ideas have largely been developed in the context of bank exposure to corporate or household borrowers, rather than sovereign entities. Our work offers some of the first direct evidence on risk-taking in sovereign derivatives.

a) Primary sovereign exposure

Although we have seen that banks were not using SovCDS to hedge the primary exposure of their bond positions in aggregate, our data do permit us to examine their trading in the context of the full exposure to each country, which includes trading-book positions in public bonds, loan-book exposure, and holdings of money-market instruments. We would expect banks to manage both instruments simultaneously. Because our specification is in differences, we use the change in each bank's total bond/loan position in each country (*LD.sovpos*). Since we are viewing CDS positions as exogenous, we lag this variable by one period.

b) Sovereign risk

The past month's log CDS spread of the sovereign (*L.logsovspread*) serves as an indication of whether banks take on or lay off risk on sovereigns based on sovereign default risk. Moreover, the contemporaneous changes of the sovereign log CDS spread (*D.logsovspread*) shows whether banks position themselves in the sovereign CDS market dynamically in response to changes in the default risk of the underlying sovereign reference entity.

c) Bank risk

We use the past month's log CDS spread of the bank (*L.logbankspread*) in order to understand how banks with a higher default risk take positions in the sovereign CDS market. As an alternative to the past month's CDS levels, we make use of contemporaneous log changes of bank CDS in the same month (*D.logbankspread*) to see whether banks that experience an increase in their default risk take significant actions in the sovereign CDS market in parallel.

d) Interaction of bank and sovereign risk

We are interested in establishing whether banks that have a higher default risk also take positions according to changes in the default risk of the sovereign. In order to identify this trend, we study the interaction between the past month's log CDS bank spread and the contemporaneous changes of the log CDS sovereign spread (*L.logbankspread* $*$ *D.logsovspread*). Similarly, we study the interaction between contemporaneous changes of the log CDS bank and sovereign spreads (*D.logbankspread* $*$ *D.logsovspread*).

e) Regulatory ratios

Banks' regulatory ratios are central to our analysis. In order to conform to and potentially "arbitrage" the regulatory capital requirements, banks undertake asset management activities, which also include sovereign risk-taking. We use the bank's Tier 1 Ratio to see whether the extent of regulatory capitalization has an effect on its sovereign CDS trading activity, which is calculated as quarterly core capital divided by the bank's risk-weighted assets (RWA). We use the quarterly lagged value for our month-level analysis (*L.regcapratio*). By using past-quarters' regulatory ratios, we ensure that the bank's monthly CDS trading activity occurs after the quarterly reporting of accounting ratios.

The ratio of risky assets based on Basel risk weights is also relevant (from the perspective of regulatory capital adequacy) in order to observe whether banks that possess a riskier balance sheet are more prone to taking on or laying off sovereign CDS inventories. The risk-weighted assets (RWA) ratio is calculated as the risk-weighted assets divided by non-bank assets (loans and advances to non-banks), whose quarterly value is also lagged with respect to the CDS trading activity (*L.rwaratio*).

f) Interactions with regulatory ratios

The interactions of both regulatory ratios with the past month's log sovereign CDS are also important for identifying whether banks that are well-capitalized or possess riskier assets (again, from the perspective of regulatory capital adequacy) undertake CDS trading for particular sovereigns that have different risk levels ($L.logsovspread * L.regcapratio$ and $L.logsovspread * L.rwaratio$).

g) Deposits

The overnight deposits of foreign banks are potentially interesting for two reasons. As a measure of wholesale funding, reliance on these deposits could have a disciplinary effect on risk-taking. On the other hand, deposit inflows could potentially induce risky balance sheet expansion. However, given the zero regulatory capital charge for SovCDS positions, it is not clear whether to expect these positions to be linked to balance sheet constraint. We scale the deposits by non-bank assets and lag the variable (*L.depov_nba*), which is available on a monthly basis.

h) CDS-bond "basis"

Due to limits to argbitrage, sovereign CDS spreads were frequently divergent from the yields-to-maturity on the government bonds of the reference nations during the crisis. This difference (defined as the 5-Year government bond yield minus the 5-Year sovereign CDS premium) is known as the "basis". Our sample period contains persistent deviations of the basis, both positive and negative, for different states. If, from the point of view of banks, the two instruments are substitutes, the basis captures a straightforward incentive to prefer one over the other. We use the value (*bond-CDS basis*) measured at the end of the observation month.

3.2 Specification

Because CDS positions of individual banks in individual countries are highly nonstationary, our dependent variable is in first differences. Thus our overall econometric design is a dynamic panel regression, in which the main bank and sovereign risk variables on the left-hand side are also in first differences and are observed simultaneously. However, we also include lagged level variables to control for omitted lag differences (similar to an error-correction specification). In addition, lagged levels are employed for low-frequency bank balance sheet and regulatory variables.

As already noted, a consequence of first-differencing is that most of our observations of the dependent variable (over 80 percent) are zero. Many banks never take positions in certain countries' CDS, and only infrequently adjust the positions they do take. This makes it very difficult to detect responses to any covariates. Our solution is to separately model (i) the likelihood that banks change their positions, and (ii) the trade amount conditional on the choice to trade. Formally, we do this via treating the zero observations as missing, and estimating a Heckman (1979) selection specification.

In addition to giving us greater power to detect the second-stage responses, the Heckman analysis also corrects for the possiblibility that, the two decisions could interact in a manner that affects inferences. Specifically, trading costs and illiquidity – which are likely to be key determinants of trading frequency (the selection stage) – will differ systematically across banks and across countries, and could be correlated with (second stage) responses to other characteristics.[10] Our procedure allows us to shed light on the separate determinants of the intensive and extensive margins of CDS positions.

The selection equation is similar to a probit model, where the dependent variable is: 0, if there is no change in inventory; or 1, otherwise. The independent selection variables we employ are (i) a dealer dummy (*dealer*): our three dealers typically trade more than non-dealers, since they are active in market making; (ii) the absolute value of the con-

[10] For example, large banks may trade more than small banks, and large banks may be less prone to risk shifting than small banks. Ignoring the correlation would then lead to underestimates of risk shifting.

temporaneous change in the sovereign CDS spread (*absdif_sov*): this ought to capture information arrival, such that positions will be more likely to change when the markets are moving significantly; (iii) the lagged dependent variable indicator (*lagdiff_ind*): being equal to zero if there was no DTCC position change in the prior month; and, (iv) an indicator equal to zero if there was no DTCC position at the start of the month (*posdtcc_ind*).

In the second stage, we then estimate the following regression, conditional on non-zero trade, to understand the economic determinants of the monthly change (from month t to $t+1$) in bank i's net CDS positions on sovereign s:

$$
\begin{aligned}
dif\_dtcc_{i,s,(t+1)-t} = \beta_0 &+ \beta_1 dif\_dtcc_{i,s,t-(t-1)} + \beta_2 logbankspread_{i,t} + \beta_3 logsovspread_{s,t} + \\
&+ \beta_4 logbankspread_{i,(t+1)-t} + \beta_5 logsovspread_{s,(t+1)-t} + \\
&+ \beta_6 logbankspread_{i,t} * logsovspread_{s,(t+1)-t} + \\
&+ \beta_7 logbankspread_{i,(t+1)-t} * logsovspread_{s,(t+1)-t)} + \\
&+ \beta_8 regcapratio_{i,t} + \beta_9 rwaratio_{i,t} + \\
&+ \beta_{10} logsovspread_{s,t} * regcapratio_{i,t} + \\
&+ \beta_{11} logsovspread_{s,t} * rwaratio_{i,t} \\
&+ \beta_{12} depov_{i,t}/nba_{i,t} + \beta_{13} sovpos_{i,s,t-(t-1)} \\
&+ \beta_{14} bondCDSbasis_{s,t} \ + \ u^{(1)}_{i,s,t}
\end{aligned}
$$

And the first stage selection equation is:

$$
\begin{aligned}
&Z_{i,s,t} = \gamma_0 + \gamma_1 dealer_i + \gamma_2 absdif\_sov_{s,t} + \gamma_3 lagdiff\_ind_{i,s.t} + \gamma_4 posdtcc\_ind_{i,s,t} + u^{(2)}_{i,s,t} \\
&trade_{i,s,t} = 1_{\{Z_{(i,s,t)}>0\}}
\end{aligned}
$$

where $u^{(1)}$ and $u^{(2)}$ have the correlation ρ. The estimation is undertaken via maximum likelihood.

We also estimate the model replacing unscaled monthly changes with the bank-level scaled (by bank assets) and sovereign-level scaled (by sovereign debt) variants to control for size effects. We also verify that our primary findings are not driven by the two-stage specification.

4 Empirical Results

4.1 Baseline Results

Table 4 presents the baseline set of results using the Heckman selection analysis. The odd-numbered columns report the estimates of the main equation (1). These condition upon the first stage (equation (2)), whose estimates can be found in the even-numbered columns.[11]

[Table (4) here]

As an initial observation, we note that the results support the use of a selection specification. The correlations between the residuals of the two stages of the regression, labelled *athrho*, are positively significant in all three specifications. For instance, the value of 0.0871 for the scaled by non-bank assets specification in column (3) corresponds to a correlation coefficient of 0.0869, which implies that ignoring selection effects could significantly bias the second-stage coefficient estimates.

Columns (2), (4) and (6) show that three of the first-stage selection equation variables, namely the dealer dummy, the lagged dependent variable indicator and the null position indicator, all play a role in determining the decision of whether to adjust bank positions, as indicated by the high significance of their estimates for all three specifications. Position changes are positively associated with being a dealer and having a non-zero position at the beginning of the month. In addition, having trading activity during the past month is negatively related to the current month's trading activity. The absolute value of the

[11] Our baseline table reports the inverse hyperbolic tangent of the correlation of the error term of equations (1) and (2) ρ as *athrho*, in order to constrain ρ within its valid limits, and for numerical stability during optimization: atanh $\rho = \frac{1}{2} ln(\frac{1+\rho}{1-\rho})$. The log-transformed standard error of the residual in the first equation is reported in our baseline table as *lnsigma* as well.

contemporaneous change in the sovereign CDS spread is positively correlated to having any trading activity; however, it is not statistically significant.

The second-stage analysis shows our main positive result: namely that sovereign CDS spreads, the risk-weighted assets ratio, and the interaction of the two have a significant effect on banks' sovereign CDS trading activity in all three specifications. The next subsection considers the interpretation of these effects in detail. For the moment, we shall note the signs of the three coefficient estimates. The two marginal effects are both negative, while the interaction effect is positive. Superficially, this would seem to suggest that banks with higher RWA ratios engage in more protection selling, and that there is more protection selling for higher-risk sovereigns. However, due to the interaction term, this is not always correct. In fact, for banks with an average or above-average RWA ratio, the sign of the *logsovspread* effect is positive. The marginal *rwaratio* effect is indeed negative - except when the level of sovereign risk is very high.

The positive marginal country risk effect shows the econometric benefits of our panel data. Even though the overall pattern of sovereign risk during the sample mirrors the average bank short CDS position (rising initially and then falling), there is enough cross-country risk variation at fixed times to refute the idea that there is a causal effect (e.g. "yield seeking") operating from credit risk to protection selling. Instead, we find that increases in risk are associated with protection buying.

In interesting contrast to the ambiguous effect of country risk itself, Table 4 shows a significantly positive effect of the bond-CDS basis, meaning that CDS selling is bigger when the CDS spread is large *relative* to the yield-to-maturity on the reference debt of the same sovereign. This suggests that basis arbitrage is one driver of bank trade.

Another interesting finding is the significant negative coefficient (in two of the three scaling versions) on deposits from foreign banks. This is suggestive of induced risk-taking. There is both cross-sectional and time-series variation in these deposits because after 2010 a flight to quality resulted in large inflows to dealer banks, but not non-dealers. We will see below that the effect here is driven by differences across groups. The magnitude of the coefficient using the raw euro specification implies that when summed across the 20 nations, the difference between a dealer bank with 15% foreign deposits and a non-dealer with 5% is associated with an additional protection selling of a non-trivial 112 EUR million per month, or 1.3 EUR billion per year.[12]

The findings in Table 4 are notable also for an absence of evidence supporting certain other hypotheses for explaining bank risk-taking in the CDS market. We find no evidence via levels, differences, or interactions in favour of bank risk - as measured by Tier 1 capital or banks' own CDS spread - driving protection selling. This does not support SovCDS as the preferred mechanism for risk-shifting activity due to banks' own riskiness. The finding suggests that the mechanisms driving risk-shifting through purchases of risky government bonds by riskier banks, identified by Acharya and Steffen (2015), do not extend to credit derivatives. (Below we will see some more supportive evidence of risk-shifting in subsamples, however).

Finally, we find no evidence that credit derivatives usage is linked to bank trading-book exposure to sovereign bond positions of the same countries. We had already seen broad evidence that SovCDS were not being used to hedge bond risks, which this result affirms. Hedging would appear here in the form of a positive coefficient. On the other hand, a negative coefficient would signal complementary use of both primary and derivative instruments to achieve desired portfolio exposures. Both effects may be at work for different banks, or the specification (i.e. using lagged differences) may lack the power to detect either one. We argue in appendix section A.2 that our RWA ratio variable does in fact allow us to indirectly capture (in levels) the banks' total sovereign exposure and show that the main explanatory power comes from the second-stage of the Heckman specification.

[12]These are the estimated latent responses conditional on trade.

4.2 Interpretation of Baseline Results

We have illustrated that at the aggregate level, our empirical specification has economically significant explanatory power. Statistically, the results primarily point us to three variables: the RWA ratio, the level of sovereign risk, and the interaction of the two. We now show that the RWA effect and the interaction term are driving the results at the aggregate level. We then consider how to interpret this effect.

Figure 4A shows a plot of the net monthly CDS activity (solid line) together with the fitted contribution from the RWA and interaction terms summed across banks and countries (and multiplied by the monthly conditional trade probability) as a dotted line. The fitted terms capture most of the time trend, as well as a considerable degree of the variation. The variance of the fitted series is 20% of the variance of the observation series. Also shown (dashed line) is the negligible net contribution of the sovereign risk term.

Figure 4B cumulates the RWA and interaction fitted terms over time, and also shows the cumulated data series again. The variance of the former series is 50% of the latter. The plot affirms that these terms are responsible for the model's explanatory power in the time series. Other significant variables in our regressions (including deposit flows and the CDS-bond basis) contribute little to the aggregate explanatory power.

[Figure (4) here]

How should the risk-weighted assets ratio in our specifications be interpreted, given that the regressions explicitly control for two conventional and direct measures of bank risk, i.e. the Tier 1 capital ratio and the banks' own CDS spread? Our answer is that it primarily measures bank-wide portfolio exposure to EU sovereign risk. In other words, two banks with the same level of lending (i.e. non-bank assets, which includes sovereign loans), the same Tier 1 capital, and the same credit spread must differ in the RWA, primarily because one has high sovereign exposure and the other has more commercial risk.[13] Note that in computing RWA, EU rules permit zero weights to be assigned to

[13] Another cause of RWA differences could be differing internal risk models. Mariathasan and Mer-

bonds, loans, and CDS exposure to sovereign risk of member nations, regardless of the actual level of risk of those assets. Thus, when controlling for risk, lower RWA should be interpreted as indicative of a higher sovereign exposure.

We directly verify this interpretation by looking at the contemporanous quarterly correlation of the RWA ratio with each bank's total sovereign exposure, including loans, bonds, and money market instruments of all sovereign entities including those (such as the U.S.) that are not in our base sample of 20 countries. Scaling this variable by non-bank assets, we find a highly significant negative correlation of -0.29 with the RWA ratio across bank-quarters in our sample. Viewed in this light, our results suggest a portfolio substitution effect that is operating at normal levels of risk. That is, banks are more inclined to sell CDS protection when their overall balance sheet exposure to sovereign risk is lower. (However, as noted above, we do not find substitution at the level of changes in individual country bond positions and CDS). While substitution is obviously not the same as hedging, it is at least consistent with some firm-level risk management. Alternatively, it may simply signal a preference by some banks for using CDS rather than bonds to achieve position objectives, perhaps because the former stay off the balance sheet.

Turning to the interaction effect, we see that it helps explain the selling that occurs at the start of the sample when CDS levels were low and simultaneously RWA ratios were high (Recall that the sign of the interaction effect is positive). The magnitude of the estimated coefficients tells us that the marginal impact of the RWA ratio on changes in CDS positions effectively vanishes at high levels of sovereign risk (i.e. over 400 basis points), and even reverses for extremely high levels. This is consistent with the scenario that the same banks that initially sold the most protection (the ones with high RWA ratios) tended to cover those positions at the height of the crisis. From Figure 4, we can see that the same effect occured during the height of the US turmoil in late 2008 and

rouche (2014) provide evidence consistent with regulatory arbitrage via risk-model manipulation by European banks during our sample period. We cannot rule out that banks' ability to "optimize" risk models is associated with less CDS protection selling, although a mechanism is not obvious.

early 2009. Again, this finding could be indicative of risk management, perhaps triggered by value-at-risk limits being breached.

The time-series pattern of the RWA effect fits with our substitution interpretation in the following sense. We know from the literature (Acharya and Steffen (2015), Becker and Ivashina (2018) and Crosignani (2021), among others) that as the crisis progressed, banks throughout the EU increasingly shifted their asset base away from commercial lending and towards EU sovereign debt. Mechanically, this would induce the downward trend in the RWA ratio that is exhibited in our sample. (Also note that this trend does not coincide with a downward trend in bank risk as measured by CDS spreads until after January 2012 (see Figure 2). Thus it appears that the decline in negative CDS exposure was another consequence of the build-up of primary sovereign assets during the crisis. By the same token, estimates of that increase in sovereign risk could be overstated if they do not take into account the concurrent decline in CDS exposure. Table IA1 in the internet appendix repeats our estimation in six subsamples to verify that the results are not driven by particular periods during the evolution of the Eurozone crisis.

5 Split Sample Analysis

We now repeat the estimation of our specification separately for dealer and non-dealer banks, and then for extremely risky countries (GIIPS) versus the rest of the countries.

5.1 Dealers and Non-Dealers

Given their distinct role as liquidity providers in the market, it is natural to ask whether banks designated as CDS dealers adjust their positions in the same way as non-dealer banks. From Figure 3, we know that both types of banks were net protection sellers during the sample period. It is quite plausible, however, that the factors leading them to do so were distinct.

Table 5 presents estimations for our specification, carried out separately for these two types of institution. Results for dealers are shown in columns (1) - (3). Columns (4) - (6)

give the non-dealer results. First-stage selection results are omitted for brevity. In these unreported results, we perceive no major differences between the banks in the first stage (apart from a less negative constant term for dealers, capturing their higher volume of trade), indicating that similar motivations drive the decision to trade.

[Table (5) here]

Conditional on trading, however, the dealers do appear different. In particular, the RWA ratio effect that drives the explanatory power of our main specification turns out not to apply to dealers. Our interpretation of a substitution effect between primary and derivative markets appears to relate to non-dealers.

By contrast, dealer banks with a safer (higher) Tier 1 regulatory ratios engage in selling protection more than those that have lower capital, whereas non-dealers have insignificant Tier 1 ratio coefficient estimates. For dealers, however, there is again an interaction effect of the opposite sign for the product of the Tier 1 ratio with log sovereign CDS levels. Taking the interaction into account, the marginal Tier 1 effect is negative only at low levels of country risk.

It is also interesting to note that the deposit variable is insignificant for the dealer sample, despite the fact that dealers were the only banks that experienced the flight-to-quality inflows. This shows that the effect we found in the full sample is being identified by cross-bank differences, not time-series differences. In particular, dealers sold more aggressively after 2010 when the deposit inflows occurred, but at a point where non-dealers were already covering their short positions.

For non-dealer banks, the point estimates for the RWA ratio coefficient and its interaction with sovereign CDS levels are higher (in absolute value) than the full-sample estimates in Table 4. This is true for all three scaling choices, although the statistical significance is diminished due to the smaller number of observations.

A final interesting result is the statistically significant positive coefficient on the bond-CDS basis for non-dealers, with no corresponding effect for dealers. This is perhaps surprising in that dealers might be expected to be more active in cross-market arbitrage. However it reinforces the picture of non-dealers viewing the CDS and bond markets as substitutes, and actively switching between the two.

5.2 Country Risk

The visual evidence from Figure 3 indicates that banks' protection selling was especially strong in CDS, referencing the countries that were most affected by the crisis ex post. Yet our intial regression evidence in Table 4 found no significant role for either levels or difference in country risk in explaining position changes.[14] To investigate this further, Table 6 presents the estimation results when the sample is broken down into CDS positions on GIIPS (columns (1) - (3)) and non-GIIPS (columns (4) - (6)) countries.

[Table (6) here]

Comparing these respective second-stage estimates across respective columns, a first observation is that the economically large RWA effect and its interaction with the sovereign CDS level are present in both cross-sections of countries. Given the high degree of variability in the GIIPS countries, and the large amount of protection selling in these names, it is perhaps not surprising that the point estimates of the coefficients are somewhat larger for this sample. However, the magnitudes for the non-GIIPS sample are not much diminished from their full-sample values in Table 4. (The only exception is the specification where positions are scaled by bank assets, in column 9).

While the second-stage results do not point to clear factors affecting trade size differences, there is a significant difference in the unconditional trade probability: 27.9% for the GIIPS sample versus 14.9% for the rest of the EU in unreported results. However, the first-stage results do not reveal reasons for this, with the effect simply showing up as a larger (less negative) intercept for GIIPS countries.

The table also indicates a significantly more negative effect of deposit flows on the

[14] Recall that the marginal effect of the sovlevel variable was actually positive when taking into account the effects of interaction terms.

selling of GIIPS SovCDS. We have already seen that the deposit inflows to dealers after 2010 appear to be related to their protection selling in this period. We now see those flows linked to selling by risky countries in particular. However, this sheds little light on the predominance of these countries in the selling activity of non-dealers. Finally, the table also reveals that the bond-CDS basis is a significant determinant of protection sales only among the high-risk GIIPS states. This is likely reflective of a much more stable basis for the non-GIIPS states (which have a monthly standard deviation of 157 basis points versus 527 basis points for the GIIPS sample), and hence fewer basis-driven trading opportunities.

Finally, Table 7 further subdivides the sample to examine the behaviour of dealer and non-dealer banks with respect to the GIIPS countries. Here we see that the main result, the RWA effect, is the strongest across all subsamples for the non-dealers when trading the risky countries' CDS. The point estimates for the RWA ratio and its interaction with sovereign CDS levels are each roughly two to four times larger than their values for the non-dealers in all countries (Table 5) or for all banks in the GIIPS countries (Table 6). For dealers, on the other hand, we now clearly see the significance of the deposit flows on their selling activity. Understanding the mechanism linking these sales to deposit flows is an interesting area for future research.

[Table (7) here]

6 Sovereign CDS and Bank Risk

Our results indicate that a number of German banks viewed the CDS market as offering a means to speculate on sovereign credit risk more readily than offered by the underlying sovereign debt market. This finding raises the question of whether the availability of credit derivatives, by expanding their investment opportunity set, actually increased bank risk-taking and strengthened the nexus between bank and sovereign credit risks.

Acharya and Steffen (2015) document a pattern in European bank equity exposure during our sample period that is consistent with speculation in sovereign exposure being passed through to the banks' residual claimants. Specifically, regressing bank stock returns on an index of GIIPS credit spreads, they find higher loadings on banks with larger sovereign bond positions. Motivated by their findings, we ask whether sovereign CDS positions have an effect on bank risk in our sample. Most of our banks do not have publicly traded equity. However, we can measure their risk by the level of credit spreads, as captured by their own CDS prices. We now ask whether sovereign CDS position changes affect banks CDS changes.[15]

Table 8 shows estimates in weekly panel regressions of the specification

$$
\begin{aligned}
dif\_logbankspread_{i,(t+1)-t} = \beta_0 + \beta_1 \; dif\_logiTraxx_{i,(t+1)-t} + \beta_2 \; dif\_logGIIPS_{i,(t+1)-t} \\
+ \beta_3 \; dtcc_{i,t} + \beta_4 \; sovpos_{i,t} + \epsilon_{i,t+1}
\end{aligned}
$$

where, for each bank, CDS positions (*dtcc*) and sovereign bond positions (*sovpos*) are summed across countries and scaled by assets. The first term on the right side controls for contemporaneous changes in corporate credit, as proxied by the iTraxx Europe index. The second term is an equal weighted average of (log) CDS spreads of the GIIPS countries. The estimation excludes weeks in March 2012 and June 2013, in which Greece exits and reenters the sample CDS.

[Table (8) here]

The estimates in the table find no significant effects for the credit spreads of CDS dealer banks. For non-dealer banks, however, we do see a significant positive relation of bank credit risk with GIIPS credit risk, consistent with sovereign risk feeding through to German banks as in Acharya and Steffen (2015). While the coefficient is small, the annualized volatility of the GIIPS index (log changes) is about 82% in our sample, implying an increase in the annual volatility of bank credit spreads of 5%.

[15]Note that our earlier results found little evidence of causality in the opposite direction: bank risk variables were largely insignificant in explaining changes in sovereign CDS positions.

From the third line, there is also evidence that these banks' positions in sovereign CDS significantly affect their own credit risk. The negative coefficient means that increased protection selling is associated with higher credit risk. No similar effect is evident from the banks' positions in the underlying sovereign debt. However, as this variable is measured only monthly, we have less power to detect its influence. We have seen that some non-dealer banks were large protection sellers for extended periods of time. The weekly impact, as quantified by the point estimate -0.14, would thus cumulate. A bank with a short position of 5% of assets held for 10 weeks would raise its own credit spread by 0.07 ($-0.14 * -0.05 * 10$) in log terms relative to a bank without such short positions. If the bank's credit spread level was 150 basis points, this would translate into an increase of 11 basis points.

In sum, although the effects are not dramatic, they are consistent with the interpretation that the risk of sovereign CDS positions amplified banks' own risk, and thus also the risks borne by the government entities who stand behind them. Notable for policy implications is the result that GIIPS countries' credit risk significantly flows through into the credit risk of non-dealer banks, and these banks' meaningfully large SovCDS underwriting also contributes to a material widening of their own CDS. Therefore, regulatory stress tests which focus on larger banks and dealers might miss out on the potential "hot spots" of bank-sovereign nexus. Since one of these non-dealer banks was in fact bailed out by the German government, it is reasonable to conclude that assessing the true exposure of taxpayers to bank risks via the sovereign risk channel requires paying attention also to the credit derivatives activity of smaller banks, and more generally, non-banks, since they too enjoy explicit or implicit government backing in the modern-day financial sectors.

7 Conclusion

This paper reports a perhaps surprising finding on bank behaviour during the Eurozone sovereign debt crisis. Despite bearing an increasing exposure to sovereign default risk through the *primary* markets (sovereign lending and bond positions) during the crisis, German banks used credit derivatives to take on even more sovereign risk. Their aggregate sovereign exposure through CDS sales reached 40 EUR billion in 2010, an amount roughly equal to one-fifth of the total Tier 1 capital of the banks.

Exploiting both cross-bank and cross-country variation, we are able to examine several hypotheses to explain this risk extension behaviour. In fact, a number of natural explanations fail. The literature on corporate CDS finds evidence of hedging by banks of credit exposures, whereas the literature on the bank-sovereign nexus shows how risk-shifting takes place through the purchasing of riskier sovereign bonds by undercapitalized banks. Surprisingly, we find no economically significant effect of bank and country risk variables on sovereign CDS positions of banks. Furthermore, we find no evidence to suggest that sovereign CDS sales are linked to changes in bond positions of the bank on the same sovereign.

Despite the latter result, we do find an economically significant channel from low overall bank exposure to sovereign risk (as captured in high values of the risk-weighted assets ratio) to more protection selling. This is consistent with some banks having a preference for derivative exposure as a substitute for bond exposure, due to an equivalent zero-risk weight privilege for sovereign bonds of EU member countries. Our estimated specifications link the protection sales during the first part of the crisis to relatively low overall sovereign bond exposure. As the crisis evolved and banks' asset portfolios became increasingly tilted towards sovereign lending exposures, they covered (but did not reverse) their short positions. At any rate, the banks' use of sovereign CDS during the sovereign debt crisis does not appear to have been driven by considerations of hedging the underlying sovereign risk exposure. Importantly, it appears to have amplified banks' own credit risk and thereby the bank-sovereign credit risk nexus.

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Figures and Tables

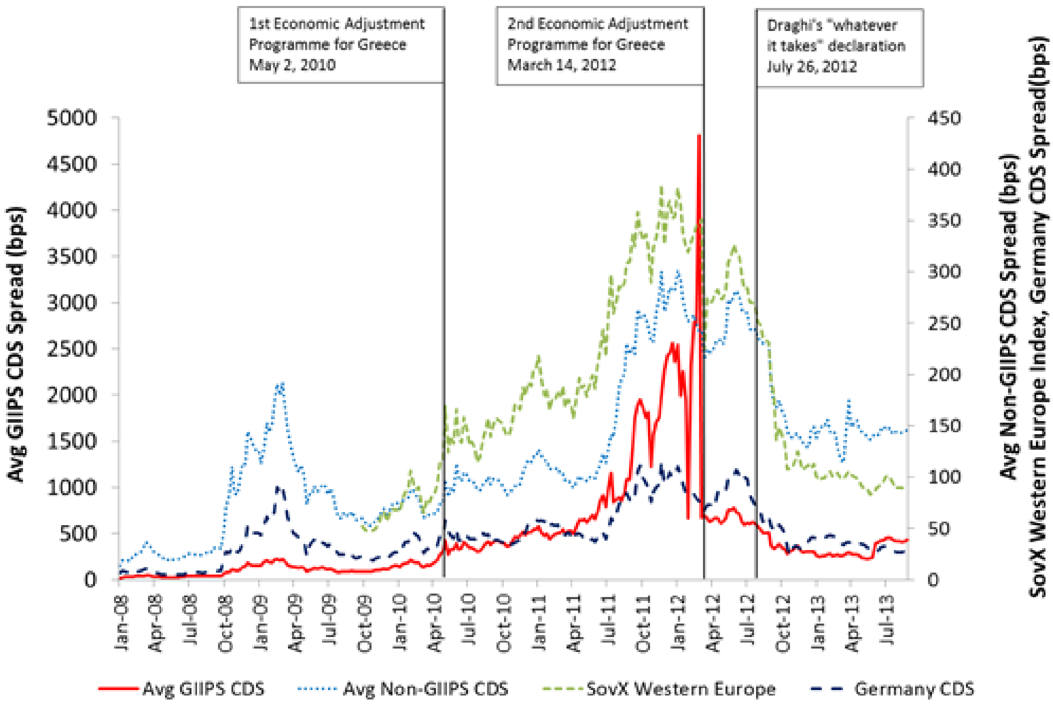

Figure 1: Sovereign CDS prices in Europe during the sovereign debt crisis.

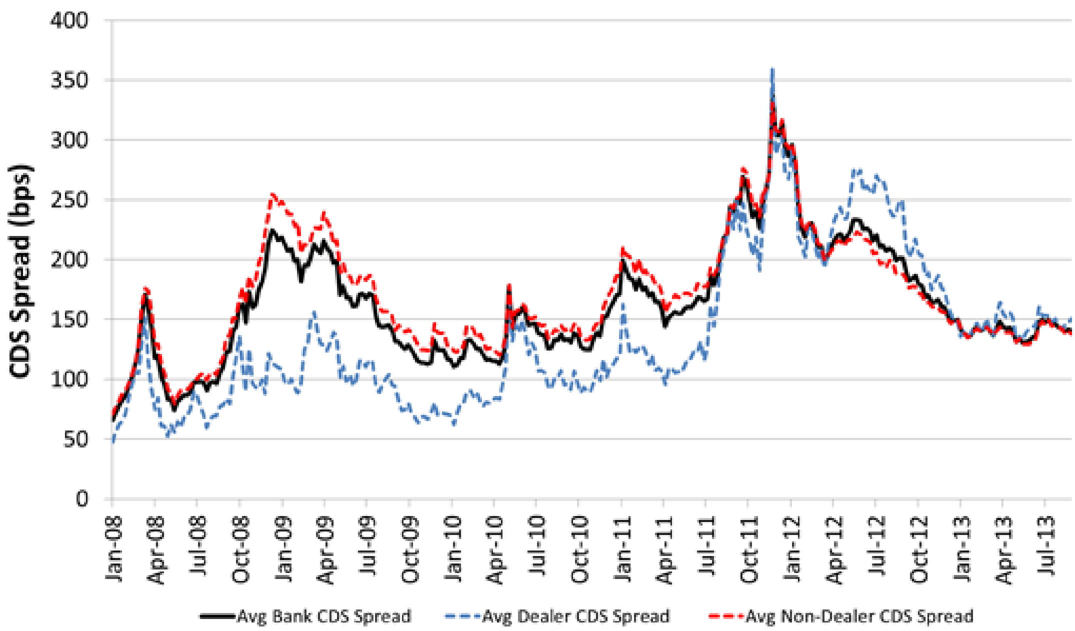

Figure 2: German bank CDS prices during the sovereign debt crisis.

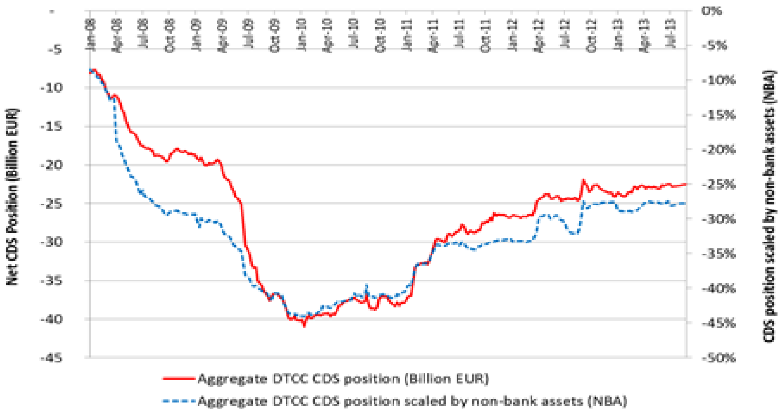

Figure 3A: Aggregate net CDS position

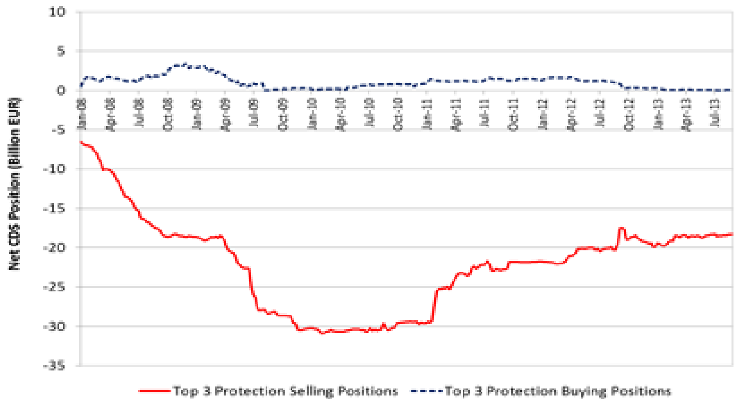

Figure 3B: Top three protection selling and purchasing positions

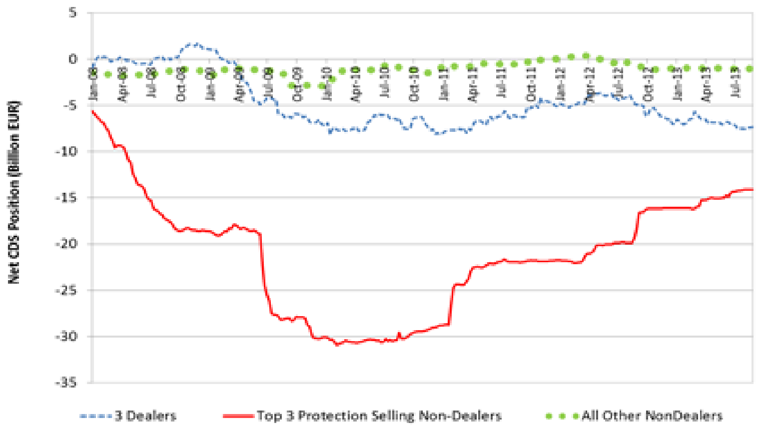

Figure 3C: Dealers vs. non-dealers

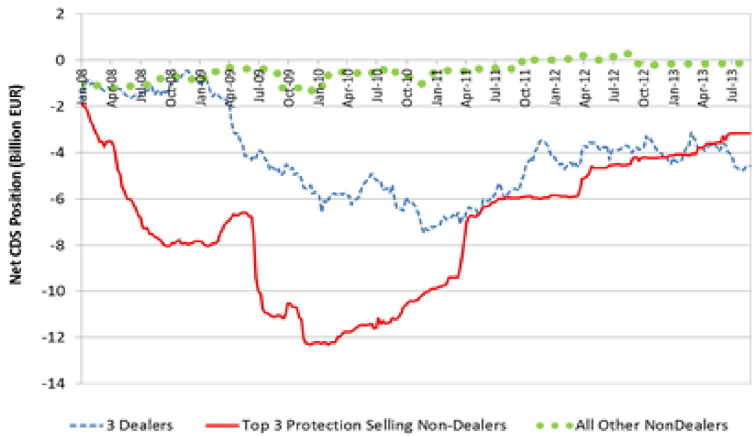

Figure 3D: Dealers vs. non-dealers (only GIIPS exposures)

Figure 3: These figures show the position-taking of German banks in the CDS market during the sovereign debt crisis. All CDS positions are aggregated across German banks (Figure 3A), across three highest protection sellers and buyers (Figure 3B), across dealers, three highest protection selling non-dealers, and all other banks (Figures 3C and 3D). Sold positions are subtracted from bought positions, in order to reach a net aggregate exposure.

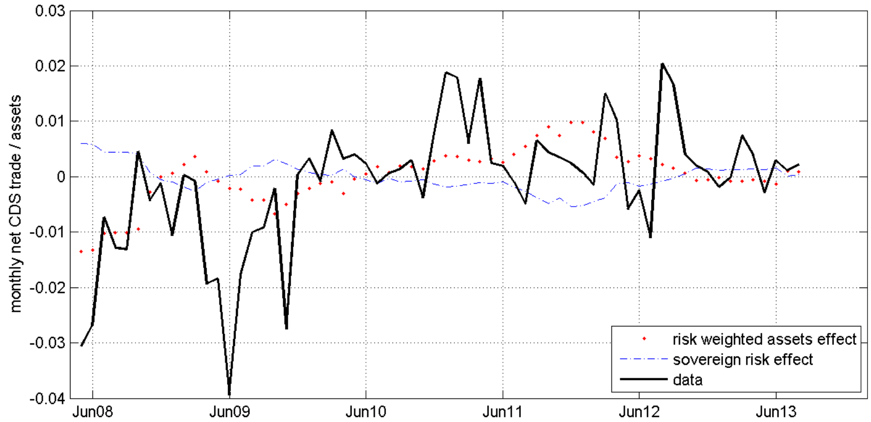

Figure 4A: This figure shows the time series of the net monthly CDS activity (solid line) together with the fitted contribution from the RWA and interaction terms summed across banks and countries which is also multiplied by the monthly conditional trade probability (dotted line). Net contribution of the sovereign CDS effect is shown as a dashed line.

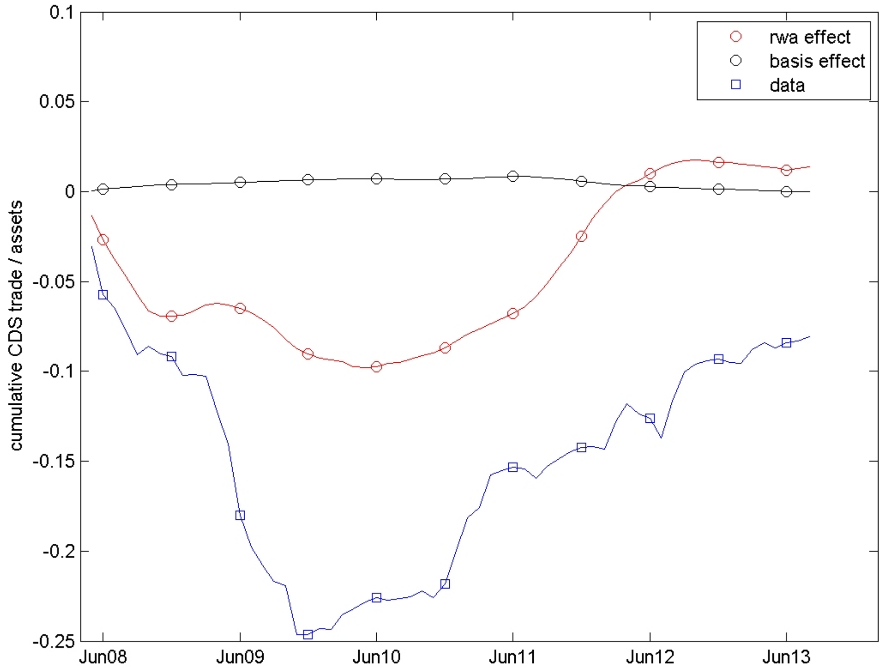

Figure 4B: This figure shows the cumulated development of the full sample averages of the RWA ratio variable multiplied by their second-stage coefficient estimate in column (3) in Table 4, and additionally by the average selection probability in Figure 5B (in circles, red); and the cumulative observed CDS positions scaled by non-bank assets as in Figure 4 (in squares, blue).

Table 1: Descriptive Statistics: Bank-Specific Variables

VARIABLES	Frequency	All banks Mean	All banks SD	Dealers Mean	Dealers SD	Non-dealers Mean	Non-dealers SD
Bank CDS spread (bps)	Weekly	162.62	118.20	137.79	67.74	169.39	127.75
Log bank CDS spread	Monthly	4.94	0.52	4.83	0.45	4.97	0.54
Log bank CDS spread differences	Monthly	0.0088	0.1816	0.0123	0.2222	0.0078	0.1687
Tier 1 ratio (%)*	Quarterly	12.20	10.87	13.14	2.88	11.99	11.98
RWA ratio (%)	Quarterly	75.24	18.32	75.08	12.06	75.28	19.50
Loans and advances to non-banks (EUR million)	Quarterly	137,758	124,192	333,791	164,263	92,520	43,457
Overnight deposits owed to non-German banks (EUR million)	Monthly	11,146	21,933	45,298	33,050	3,264	3,066
Overnight deposits owed to non-German banks / Loans and advances to non-banks (%)	Monthly	5.34	5.37	12.34	4.56	3.72	4.10

This table reports summary statistics of bank-specific variables that are used in the analysis. The full sample encompasses the European debt crisis period of January 2008 to August 2013. "Bank CDS" is retrieved from the Markit database as the composite price of 5YR Senior EUR MR CDS. "Overnight deposits owed to non-German banks" and "Loans and advances to non-banks" are retrieved from the monthly balance sheet statistics of the Bundesbank. "Tier 1 ratio" is calculated as the quarterly core capital divided by risk-weighted assets of the bank. "RWA ratio" is calculated as the risk-weighted assets divided by non-bank assets (Loans and advances to non-banks). *The high standard deviation of the Tier 1 ratio arises from an outlier bank which was bailed out and had a significant reduction in risk-weighted assets. The outlier values which occur during the final year of our sample have a Tier 1 regulatory ratio of more than 100% for this particular bank. When we exclude these values, the standard deviation of the ratio drops to 4%.

Table 2: Descriptive Statistics: DTCC CDS and Bond Holdings and Sovereign Variables

VARIABLES	Frequency	All banks Mean	All banks SD	Dealers Mean	Dealers SD	Non-dealers Mean	Non-dealers SD
Panel A: Sovereign CDS positions							
DTCC (net) (EUR million)	Weekly	-84.03	366.46	-77.83	408.35	-85.46	356.08
DTCC differences (net) (EUR million)	Monthly	-0.69	41.62	-0.19	67.10	-0.40	33.05
DTCC/non-bank assets (%)	Weekly	-0.102	0.530	-0.036	0.114	-0.117	0.584
DTCC/non-bank assets differences (%)	Monthly	-0.0008	0.0403	-0.0004	0.0190	0.0009	0.0438
DTCC/sovereign debt (%)	Weekly	-0.025	0.112	-0.005	0.167	-0.030	0.094
DTCC/sovereign debt differences (%)	Monthly	-0.0001	0.0261	-0.0007	0.0420	0.0001	0.0207
DTCC (without zero positions) (net EUR million)	Weekly	-176.61	515.65	-91.30	440.89	-219.78	544.56
DTCC (without zero positions)/non-bank assets (%)	Weekly	-0.214	0.752	-0.042	0.123	-0.301	0.907
DTCC (without zero positions)/sovereign debt (%)	Weekly	-0.053	0.157	-0.006	0.180	-0.077	0.138
Panel B: Sovereign CDS prices and bond holdings							
Sovereign CDS (across all countries and weeks) (bps)	Weekly	209.75	619.05	209.75	619.05	209.75	619.05
Log sovereign CDS spread	Monthly	4.51	1.21	4.51	1.21	4.51	1.21
Log sovereign CDS spread differences	Monthly	0.03	0.26	0.03	0.26	0.03	0.26
Sovereign bond holdings (net) (EUR million)	Monthly	231.02	785.81	199.26	840.95	238.35	772.37

This table reports summary statistics of country and bank-country pair-specific variables that are used in the analysis. The full sample encompasses the European debt crisis period of January 2008 to August 2013. "DTCC" stands for the net CDS holdings of German banks averaged across all weeks and countries. "Non-bank assets" are the loans and advances to non-banks by the corresponding bank, retrieved from the Bundesbank's monthly balance sheet statistics. "Sovereign debt" of the corresponding country is retrieved from Eurostat. "Without zero positions" assumes there is no data for unreported CDS balances instead of a value of zero. "Sovereign CDS" is retrieved from the Markit database as the composite price of 5YR Senior USD CR CDS. "Sovereign bond holdings" is the net holdings of the German banks of a given country, retrieved from the Bundesbank's statistics.

Table 3: German Bank Fraction of Open Net Positions from the Global DTCC Sample

Country	Global DTCC Sample Net Notionals	German Bank Aggregate Net Notionals	German Bank Fraction of Open Positions (%)
Austria	4,302,548,662	-1,648,696,165	38
Belgium	3,239,327,435	-803,721,952	25
Cyprus	270,194,278	-7,379,802	3
Denmark	1,987,603,981	-970,258,364	49
Finland	2,164,606,789	-916,628,406	42
France	13,032,117,831	-1,992,608,266	15
Germany	13,201,614,140	-5,297,467,476	40
Hungary	1,586,374,824	20,000,000	1
Ireland	2,317,616,182	-411,204,200	18
Italy	18,208,149,909	-4,573,611,810	25
Netherlands	3,182,248,578	-1,019,764,172	32
Norway	799,913,917	-373,700,546	47
Poland	1,190,838,071	-313,795,008	26
Portugal	3,498,465,823	-1,031,742,150	29
Slovenia	730,601,793	90,499,351	12
Spain	10,248,417,106	-1,815,963,180	18
Sweden	1,652,786,983	-827,589,410	50
UK	6,144,169,982	-591,471,984	10

This table reports the (i) outstanding net notionals in DTCC's global TIW sample on each European nation as at the end date of our sample (August, 30, 2013) in Euros, (ii) outstanding net notionals of German banks on each European nation as at the same end date of our sample in Euros, (iii) the fraction of German banks' open net positions (ii), to the global open net positions (i) as at August 30, 2013. Among our 20 European nations, Malta did not have any open positions, whereas Greece's CDS market was frozen due to the restructuring that took place in March 2012.

Table 4: Heckman Regressions (Baseline Results)

VARIABLES	(1) dif_dtcc	(2) select	(3) dif_dtcc_nba	(4) select	(5) dif_dtcc_debt	(6) select
LD.dtcc	0.178*** (0.000)					
LD.dtcc_nba			0.346*** (0.000)			
LD.dtcc_debt					0.0474 (0.180)	
L.logbankspread	0.345 (0.425)		-0.483 (0.470)		-0.00568 (0.983)	
D.logbankspread	-0.404 (0.745)		-1.04 (0.183)		-1.22** (0.017)	
L.logsovspread	-2.60*** (0.000)		-0.716 (0.196)		-1.67** (0.044)	
D.logsovspread	-13.3 (0.185)		-17.9 (0.136)		-3.67 (0.284)	
L.logbankspread$*$ D.logsovspread	3.08 (0.144)		3.97 (0.117)		0.993 (0.156)	
D.logbankspread$*$ D.logsovspread	-2.56 (0.305)		-0.129 (0.946)		-0.288 (0.856)	
L.regcapratio	15.2 (0.449)		13.6 (0.292)		3.75 (0.797)	
L.rwaratio	-22.6*** (0.000)		-10.2*** (0.010)		-12.8*** (0.000)	
L.logsovspread$*$ L.regcapratio	0.590 (0.890)		-0.829 (0.757)		0.816 (0.788)	
L.logsovspread$*$ L.rwaratio	4.05*** (0.000)		1.65** (0.047)		2.37*** (0.002)	
L.depov_nba	-5.13* (0.063)		-1.05 (0.690)		-3.66*** (0.007)	
LD.sovpos	4.11 (0.487)		12.6 (0.679)		-1.40 (0.822)	
bond-CDS basis	0.000595* (0.083)		0.000514** (0.028)		0.00000136 (0.996)	
dealer		0.589**** (0.000)		0.587*** (0.000)		0.588*** (0.000)
absdif_sov		0.827 (0.222)		0.832 (0.219)		0.833 (0.218)
lagdiff_ind		-1.07*** (0.000)		-1.08**** (0.000)		-1.07*** (0.000)
posdtcc_ind		1.39*** (0.000)		1.39*** (0.000)		1.40*** (0.000)
athrho	0.162*** (0.000)		0.100 (0.023)		0.0890*** (0.002)	
lnsigma	18.4*** (0.000)		-7.44 (0.000)		-7.51*** (0.000)	
Constant	9.98*** (0.004)	-1.43*** (0.000)	5.89 (0.126)	-1.43*** (0.000)	7.99** (0.042)	-1.43*** (0.000)
Observations	20,027	20,027	20,027	20,027	20,027	20,027

This table presents the estimates of the Heckman regressions with the full sample. Columns (1-2) refer to the results without scaling (raw euros), (3-4) are scaled by non-bank assets (loans and advances to non-banks), and (5-6) are scaled by sovereign debt. Columns (2), (4) and (6) contain the first-stage selection results, and columns (1), (3) and (5) contain the second-stage main regressions. Bank and sovereign CDS spreads are log-scaled. “L” stands for time t spread, and “D” stands for the $(t+1)-(t)$ contemporaneous differences in spreads. Interaction variables are composed with levels (at time t) or at contemporaneous differences ($[t+1]-t$) interchangeably. “regcapratio” is calculated as the quarterly Tier 1 core capital divided by risk-weighted assets of the bank. “rwaratio” is calculated as the risk-weighted assets divided by non-bank assets. The independent variables “L.logbankspread”, “D.logbankspread”, “L.logsovspread”, “D.logsovspread”, “banklevel_sovdiffs”, “bankdiffs_sovdiffs”, “L.regcapratio”, “L.rwaratio”, “sovlevel_regcap”, “sovlevel_rwaratio”, “L.depov_nba”, “bond-CDS basis” and the regression constant are presented in e+07 for column (1) and in e-04 for columns (3) and (5). The independent variable “LD.sovpos” is presented in e-03 for column (1) and in e-15 for columns (3) and (5). The selection variable “absdif_sov” is presented in e-04 in columns (2), (4) and (6). All errors are robust clustered at the bank-country pair level. ***, **, * denote statistical significances at 99%, 95% and 90% levels. P-values are in parentheses.

Table 5: Heckman Regressions (Dealers vs. Non-Dealers)

	Dealers			Non-dealers		
VARIABLES	(1) dif_dtcc	(2) dif_dtcc_nba	(3) dif_dtcc_debt	(4) dif_dtcc	(5) dif_dtcc_nba	(6) dif_dtcc_debt
LD.dtcc	0.0882			0.328***		
	(0.272)			(0.000)		
LD.dtcc_nba		0.206***			0.366***	
		(0.004)			(0.000)	
LD.dtcc_debt			-0.0206			0.259***
			(0.389)			(0.000)
L.logbankspread	0.274	0.0169	-0.128	1.02	-0.790	0.245
	(0.663)	(0.89)	(0.589)	(0.146)	(0.537)	(0.583)
D.logbankspread	0.413	0.0837	-0.942	-0.488	-2.42	-1.10
	(0.771)	(0.802)	(0.169)	(0.821)	(0.264)	(0.231)
L.logsovspread	-2.11**	-0.896***	-2.24	-4.35***	-1.57	-2.35***
	(0.039)	(0.001)	(0.123)	(0.004)	(0.450)	(0.008)
D.logsovspread	-29.9	-2.40	-10.6*	0.272	-33.3	-0.716
	(0.136)	(0.648)	(0.072)	(0.975)	(0.150)	(0.890)
L.logbankpread∗	6.28	0.496	2.26*	0.480	7.46	0.522
D.logsovspread	(0.138)	(0.646)	(0.065)	(0.786)	(0.127)	(0.616)
D.logbankpread∗	-0.0534	0.314	0.211	-10.8*	-5.21	-2.07
D.logsovspread	(0.985)	(0.709)	(0.919)	(0.059)	(0.383)	(0.493)
L.regcapratio	-66.2*	-24.4***	-37.6	14.3	0.118	-9.09
	(0.051)	(0.007)	(0.150)	(0.650)	(0.997)	(0.654)
L.rwaratio	-4.08	-2.65	-6.80	-31.3***	-16.7*	-14.5***
	(0.376)	(0.103)	(0.121)	(0.000)	(0.070)	(0.001)
L.logsovspread∗	15.3**	5.48***	8.42	3.15	2.27	4.76
L.regcapratio	(0.046)	(0.005)	(0.146)	(0.617)	(0.733)	(0.250)
L.logsovspread∗	0.436	0.418	1.54	5.73***	2.54	2.71***
L.rwaratio	(0.659)	(0.184)	(0.136)	(0.000)	(0.205)	(0.002)
L.depov_nba	-3.67	0.382	1.08	11.1	21.1*	-3.20
	(0.367)	(0.830)	(0.791)	(0.176)	(0.097)	(0.424)
LD.sovpos	5.98	19.5	-0.852	-4.72	-9.91	3.18
	(0.318)	(0.535)	(0.880)	(0.604)	(0.880)	(0.931)
bond-CDS basis	0.000490	0.0000619	-0.000382	0.000760**	0.00123**	0.000502***
	(0.453)	(0.658)	(0.404)	(0.017)	(0.013)	(0.008)
Constant	8.11*	3.88***	9.87*	14.8**	12.1	9.70**
	(0.058)	(0.001)	(0.094)	(0.039)	(0.248)	(0.037)
Observations	3,687	3,687	3,687	16,340	16,340	16,340

This table presents the estimates of the second-stage main Heckman regressions split into dealers and non-dealers samples. Columns (1-3) refer to the results with the dealers, and (4-6) are the results with non-dealers. First-stage selection results are omitted for brevity. All variables are defined as in Table 4. The independent variables "L.logbankspread", "D.logbankspread", "L.logsovspread", "D.logsovspread", "banklevel_sovdiffs", "bankdiffs_sovdiffs", "L.regcapratio", "L.rwaratio", "sovlevel_regcap", "sovlevel_rwaratio", "L.depov_nba", "bond-CDS basis" and the regression constant are presented in e+07 for column (1) and (4), and in e-04 for columns (2), (3), (5) and (6). The independent variable "LD.sovpos" is presented in e-03 for column (1) and (4) and in e-15 for columns (2), (3), (5) and (6). All errors are robust clustered at the bank-country pair level. ***, **, * denote statistical significances at 99%, 95% and 90% levels. P-values are in parentheses.

Table 6: Heckman Regressions (GIIPS vs. Non-GIIPS)

	GIIPS			Non-GIIPS		
VARIABLES	(1) dif_dtcc	(2) dif_dtcc_nba	(3) dif_dtcc_debt	(4) dif_dtcc	(5) dif_dtcc_nba	(6) dif_dtcc_debt
LD.dtcc	0.229*** (0.000)			0.0662 (0.397)		
LD.dtcc_nba		0.208*** (0.000)			0.431*** (0.911)	
LD.dtcc_debt			0.169* (0.054)			0.002 (0.901)
L.logbankspread	0.556 (0.514)	0.363 (0.689)	-0.433 (0.335)	0.0658 (0.908)	-0.911 (0.364)	-0.0409 (0.899)
D.logbankspread	0.797 (0.722)	-0.345 (0.698)	-1.64** (0.019)	-1.24 (0.310)	-1.54 (0.191)	-1.24 (0.141)
L.logsovspread	-2.26** (0.034)	-1.50** (0.046)	-1.03* (0.087)	-3.39*** (0.003)	0.00998 (0.992)	-3.06 (0.079)
D.logsovspread	-17.7 (0.342)	-5.62 (0.588)	-4.03 (0.424)	-5.44 (0.449)	-28.1 (0.172)	-5.07 (0.291)
L.logbankspread∗ D.logsovspread	4.22 (0.286)	1.392 (0.512)	1.09 (0.272)	1.37 (0.363)	6.11 (0.16)	1.31 (0.19)
D.logbankspread∗ D.logsovspread	-9.62*** (0.009)	-4.46 (0.168)	-2.32 (0.270)	1.11 (0.712)	2.28 (0.307)	1.50 (0.526)
L.regcapratio	73.0 (0.132)	60.4* (0.074)	25.1 (0.254)	-8.97 (0.718)	-0.0651 (0.997)	-23.4 (0.399)
L.rwaratio	-31.0*** (0.000)	-22.8*** (0.000)	-15.6*** (0.005)	-21.9*** (0.000)	-1.98 (0.751)	-14.8** (0.014)
L.logsovspread∗ L.regcapratio	-9.21 (0.292)	-9.36 (0.114)	-4.20 (0.298)	4.61 (0.388)	2.01 (0.638)	6.59 (0.288)
L.logsovspread∗ L.rwaratio	5.44*** (0.001)	4.03*** (0.001)	2.82*** (0.005)	4.23*** (0.001)	0.00257 (0.999)	3.07** (0.033)
L.depov_nba	-8.40 (0.120)	-6.21* (0.055)	-4.82** (0.017)	-1.92 (0.552)	3.34 (0.399)	-2.80 (0.126)
LD.sovpos	13.9 (0.418)	75.7 (0.407)	12.6 (0.442)	12.3 (0.445)	-8.83 (0.362)	-3.41 (0.528)
bond-CDS basis	0.00114** (0.048)	0.000500** (0.029)	0.000474*** (0.001)	-0.000466 (0.722)	0.000371 (0.750)	-0.00164 (0.271)
Constant	7.54 (0.247)	6.38 (0.276)	8.02** (0.046)	14.3** (0.020)	3.76 (0.543)	13.8* (0.089)
Observations	4,885	4,885	4,885	15,142	15,142	15,142

This table presents the estimates of the second-stage main Heckman regressions split into GIIPS and non-GIIPS samples. Columns (1-3) refer to the results for GIIPS countries, and (4-6) are the results for non-GIIPS countries. First-stage selection results are omitted for brevity. All variables are defined as in Table 4. The independent variables "L.logbankspread", "D.logbankspread", "L.logsovspread", "D.logsovspread", "banklevel_sovdiffs", "bankdiffs_sovdiffs", "L.regcapratio", "L.rwaratio", "sovlevel_regcap", "sovlevel_rwaratio", "L.depov_nba", "bond-CDS basis" and the regression constant are presented in e+07 for column (1) and (4), and in e-04 for columns (2), (3), (5) and (6). The independent variable "LD.sovpos" is presented in e-03 for column (1) and (4), and in e-15 for columns (2), (3), (5) and (6). All errors are robust clustered at the bank-countries pair level. ***, **, * denote statistical significances at 99%, 95% and 90% levels. P-values are in parentheses.

Table 7: Heckman Regressions (GIIPS Dealers vs. GIIPS Non-Dealers)

	GIIPS & Dealers			GIIPS & Non-dealers		
VARIABLES	(1) dif_dtcc	(2) dif_dtcc_nba	(3) dif_dtcc_debt	(4) dif_dtcc	(5) dif_dtcc_nba	(6) dif_dtcc_debt
LD.dtcc	0.156** (0.001)			0.360*** (0.000)		
LD.dtcc_nba		0.276*** (0.000)			0.263*** (0.002)	
LD.dtcc_debt			-0.0433 (0.275)			0.312*** (0.000)
L.logbankspread	-0.0372 (0.976)	-0.077 (0.77)	-0.534 (0.145)	1.73 (0.218)	1.22 (0.46)	-0.0847 (0.909)
D.logbankspread	2.65 (0.392)	0.276 (0.622)	-0.976 (0.267)	-1.75 (0.385)	-0.791 (0.699)	-1.58 (0.114)
L.logsovspread	2.71*** (0.000)	-0.352 (0.283)	0.407 (0.608)	-8.51*** (0.000)	-6.83*** (0.001)	-4.43** (0.019)
D.logsovspread	-42.03 (0.368)	0.638 (0.951)	-6.50 (0.500)	-6.33 (0.598)	-13.4 (0.401)	-6.88 (0.405)
L.logbankspread∗ D.logsovspread	9.22 (0.356)	0.0317 (0.988)	1.39 (0.466)	1.82 (0.449)	3.11 (0.337)	1.77 (0.284)
D.logbankspread∗ D.logsovspread	-4.48 (0.465)	-1.43 (0.327)	-2.63 (0.277)	-14.9** (0.032)	-13.0* (0.087)	-1.94 (0.641)
L.regcapratio	61.9* (0.051)	-4.72 (0.647)	14.1 (0.554)	62.4 (0.643)	55.4 (0.582)	-6.47 (0.872)
L.rwaratio	-2.90 (0.747)	-3.84* (0.093)	-4.65 (0.293)	-64.4*** (0.000)	-50.8*** (0.000)	-31.3*** (0.008)
L.logsovspread∗ L.regcapratio	-8.15 (0.261)	1.96 (0.36)	-2.60 (0.559)	-4.59 (0.828)	-4.33 (0.794)	2.96 (0.669)
L.logsovspread∗ L.rwaratio	-0.848 (0.633)	0.54 (0.157)	0.607 (0.480)	11.6*** (0.000)	9.52*** (0.000)	5.85*** (0.007)
L.depov_nba	-23.8*** (0.001)	-1.94 (0.648)	-6.74** (0.047)	13.0 (0.434)	-6.01 (0.728)	-6.44 (0.383)
LD.sovpos	16.9 (0.434)	69.6 (0.545)	-3.79 (0.875)	14.5 (0.150)	120.0 (0.109)	95.9** (0.017)
bond-CDS basis	0.00161 (0.177)	0.000273 (0.157)	0.000289*** (0.003)	0.000763* (0.060)	0.000812** (0.040)	0.000658*** (0.005)
Constant	-11.2 (0.218)	1.82 (0.271)	1.70 (0.675)	36.2*** (0.008)	28.0** (0.039)	24.1** (0.022)
Observations	925	925	925	3,960	3,960	3,960

This table presents the estimates of the second-stage main Heckman regressions for GIIPS countries only, split into dealer and non-dealer samples. Columns (1-3) refer to the results with the dealer activity on GIIPS countries, and (4-6) are the results with the non-dealer activity on GIIPS countries. First-stage selection results are omitted for brevity. All variables are defined as in Table 4. The independent variables "L.logbankspread", "D.logbankspread", "L.logsovspread", "D.logsovspread", "banklevel_sovdiffs", "bankdiffs_sovdiffs", "L.regcapratio", "L.rwaratio", "sovlevel_regcap", "sovlevel_rwaratio", "L.depov_nba", "bond-CDS basis" and the regression constant are presented in e+07 for column (1) and (4), and in e-04 for columns (2), (3), (5) and (6). The independent variable "LD.sovpos" is presented in e-03 for column (1) and (4), and in e-15 for columns (2), (3), (5) and (6). All errors are robust clustered at the bank-country pair level. ***, **, * denote statistical significances at 99%, 95% and 90% levels. P-values are in parentheses.

Table 8: Bank Credit Risk and Sovereign CDS Exposure

	Dealers	Non-dealers
	(1)	(2)
VARIABLES	D.logbankspread	D.logbankspread
D.logiTraxx	0.86***	0.27***
	(0.00)	(0.00)
D.logGIIPS	0.04	0.06**
	(0.30)	(0.03)
L.dtcc	0.18	-0.14*
	(0.75)	(0.08)
L.sovpos	0.19	0.02
	(0.59)	(0.60)
Observations	840	3,030
R^2	0.70	0.20

The table shows estimates of the panel specification (1). Robust standard errors are clustered by time. p-values are reported in parentheses.

A Appendix

A.1 DTCC Data Usage in Academic Finance Literature

Table A1: Usage of DTCC Transaction and Position Data in the recent literature

Paper	Confidentiality	Data Aggregation	Whose Position	On which Reference Entities	Time Interval
Gündüz, Ongena, Tümer-Alkan, and Yu (2017)	Proprietary	Individual Position	German banks	European corporates	2008-2010
Gündüz (2018)	Proprietary	Individual Transaction & Position	German banks	Global financial institutions	2006-2012
Gehde-Trapp, Gündüz, and Nasev (2015)	Proprietary	Individual Transaction	German banks	German corporates & financial institutions	2001-2014
Siriwardane (2019)	Proprietary	Individual Position	US banks	US corporates & financial institutions	2010-2016
Czech (2021)	Proprietary	Individual Position	UK banks	UK corporates & financial institutions	2014-2016
Duffie, Scheicher, and Vuillemey (2015)	Proprietary	Individual Position	Global banks	European sovereigns & financial institutions	Snapshot of end-2011
Peltonen, Scheicher, and Vuillemey (2014)	Proprietary	Individual Position	Global banks	European sovereigns & financial institutions	Snapshot of end-2011
Oehmke and Zawadowski (2017)	Free Access	Aggregate Position	-	Global corporates	2008-2012
Augustin, Sokolovski, Subrahmanyam, and Tomio (2021)	Free Access	Aggregate Position	-	Global sovereigns	2008-2015
Berg and Streitz (2012)	Free Access	Aggregate Position	-	Global sovereigns	2008-2010
This paper: **Acharya, Gündüz and Johnson (2022)**	Proprietary	Individual Position	German banks	European sovereigns	2008-2013

A.2 The RWA Ratio and its Explanatory Power

In this section we argue that our RWA ratio variable does in fact allow to indirectly capture the banks' total sovereign exposure. Despite the negative results, our specification does succeed overall in explaining an economically significant fraction of the aggregate pattern of CDS protection selling observed in the sample. We can quantify this in the context of the Heckman specification by combining the explanatory power of the first and second stages. Specifically using the fitted coefficients, we define the expected change in the DTCC position for bank i, country s, and month t to be:

$$\widehat{yexp}_{i,s,t} = \mathbb{E}\big[y_{i,s,t} \mid y^{observed}_{i,s,t}\big] * Pr(y^{observed}_{i,s,t})$$

Figure A1 shows the fit over the course of the sample by aggregating these values in each month across banks and sovereigns $(\sum_{i,s} \widehat{yexp}_{i,s,t})$ and then cumulating over months, starting with January 2008. The plot uses the non-bank-assets scaled specification (results for the other specification are similar). The model's fit follows the same time-series pattern as the aggregate data (also plotted) of an initial sustained selling phase, followed by a gradual covering of short positions. The fitted model accounts for 12.5% of the variation in the aggregate cumulated series.

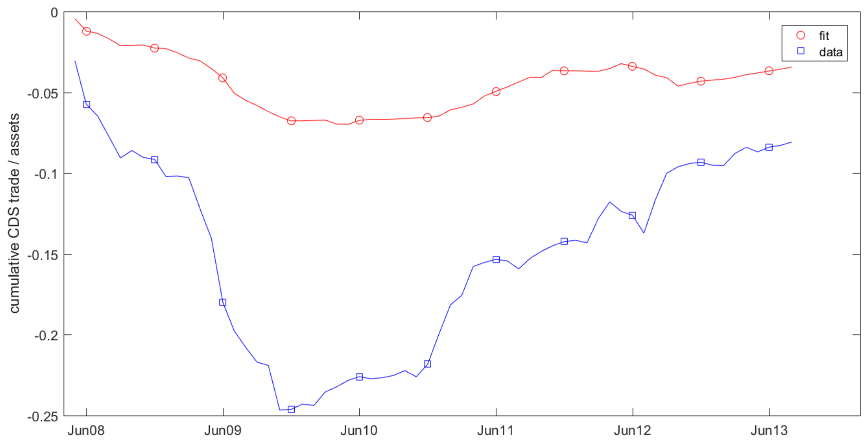

Figure A1: (Cumulated) Predicted vs. Observed Values in Heckman Analysis

How much of the explanatory power in the time series is attributable to the selection equation, and how much stems from the second stage? The next two figures decompose into the monthly contribution to $\widehat{yexp}_{i,s,t}$ from the second-stage regression (Figure A2) and the first-stage probit (Figure A3). The second-stage contribution comes from the expected value of the dependent variable, conditional on the dependent variable being observed, that is:

$$\widehat{ycond}_{i,s,t} = \mathbb{E}\big[y_{i,s,t} \mid y^{observed}_{i,s,t}\big]$$

and as $\widehat{ycond}_{i,s,t}$ is aggregated across banks and sovereigns in a given month, the time series for Figure A2 is $(\sum_{i,s} \widehat{ycond}_{i,s,t})$. The selection probability for each bank i, sovereign s, at month t is:

$$\widehat{yexp}_{i,s,t}/\widehat{ycond}_{i,s,t}$$

which constitutes the time series in Figure A3 after averaging across bank and sovereigns.

The main effect of the selection equation is a dampening of the expected activity over time. In Figure A3, we observe that the mean trade probability dropped from a peak of almost 30% to less than 15% at the end of our sample. Due to this dampening, the second-stage conditional expectation predicts a lower degree of protection purchase, particularly near the end of the sample. This result is not surprising, since having positions is one of the main drivers of position adjustments (*posdtcc_ind*), and our sample banks closed out most of their positions over the period (see Figure 3).

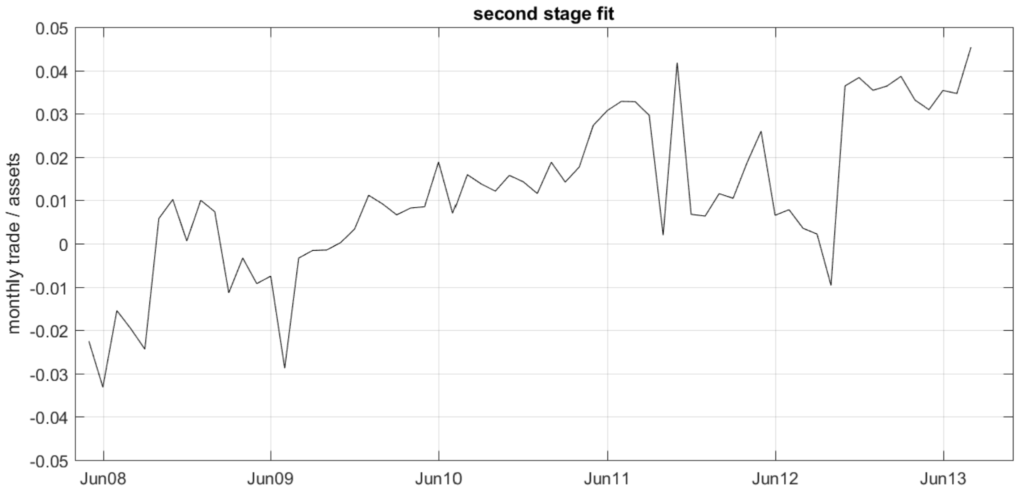

Figure A2: This figure shows the fit of the second stage of the Heckman regression to the observed dependent variable (DTCC changes scaled by non-bank assets), where the y-axis indicates $\widehat{ycond}_{i,s,t} = \mathbb{E}\left[y_{i,s,t} \mid y_{i,s,t}^{observed}\right]$. We sum across bank-country pairs in each observation month.

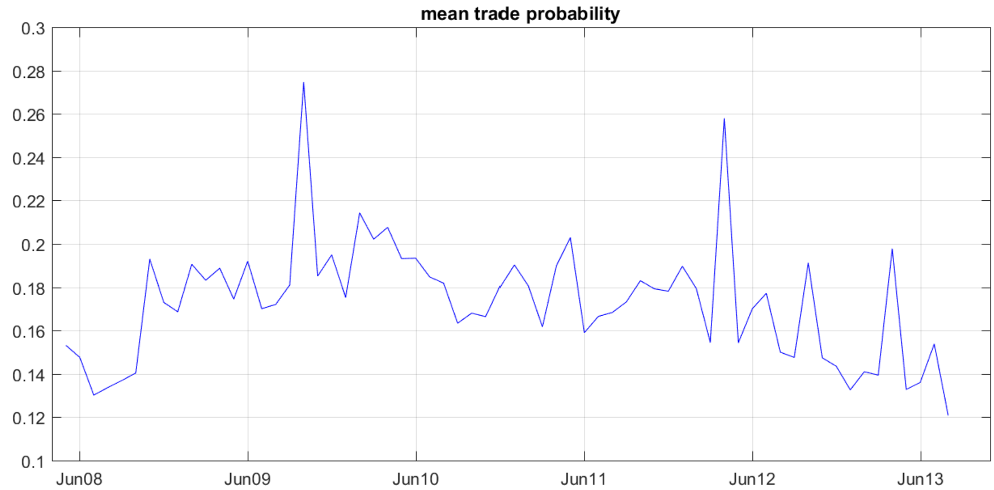

Figure A3: This figure shows the selection probability for each bank i, sovereign s, at month t, calculated as $\widehat{yexp}_{i,s,t}/\widehat{ycond}_{i,s,t}$ and depicts the time series below after averaging across bank and sovereigns.

However, the primary explanatory power comes from the second stage. Quantitatively, the fraction of the variance in the second-stage analysis that is explained by the conditional expectation series when the latter is multiplied by a constant probability of observation (thus shutting down the selection dynamics) is 71%.

Second-stage inferences in the Heckman framework can be sensitive to misspecification of the selection model (Briggs (2004)). We have verified that our main findings are robust to alternative first-stage specifications including the bond-CDS basis, total sovereign debt, and an indicator for GIIPS countries.[16] In particular, the second stage still yields statistically significant estimates (of the same sign) for the RWA coefficient and the interaction of RWA with the level of sovereign CDS spreads. Further, ordinary least-squares (OLS) estimation in the sample of non-zero observations yields similar point estimates for the conditional responses. In addition, OLS estimation on the sample that includes the zero observations, while biasing all the responses towards zero, preserves the sign and statistical significance of the RWA effect.

The standard errors in Table 4 use clustering at the bank-country level. Our inferences are unchanged when we cluster at the bank or country level separately. In addition, the findings are also robust to bank outlier effects. In unreported results, we find that the RWA channel is actually stronger after removing a bank (West LB), whose 85 EUR billion worth of toxic assets were transferred in November 2009 to create Germany's first "bad bank" in an attempt to restructure the financial institution and prevent systemic effects.

[16]These results are omitted for brevity but are available upon request. We thank Mike Mariathasan for calling our attention to this point.

B Internet Appendix

B.1 Robustness over Time

Table IA1 looks at six subsamples to verify that the results are not driven by particular periods during the evolution of the Eurozone crisis. The first four sample breakpoints are the dates of the ECB's stress tests. The final breakpoint is the effective date of the ESMA ban on uncovered long positions in sovereign bonds of EU member countries. For brevity, the table reports only the second-stage regression results, and only use the NBA scaling for each period.

An initial finding of the table is that the RWA effect (both the negative coefficient and the positive interaction with the level of bank CDS) is not driven by a single period. Except for the (brief) period between the first and second stress tests, the signs are preserved, and statistical significance is strong in four of the periods, including the first and last. It also remains true that there is no consistent evidence of yield-chasing behaviour in the sample. Some periods - particularly after September 2011 - do show evidence consistent with risk-shifting via negative coefficients on levels or differences of banks' own CDS rate.

The period of the ESMA ban does exhibit some different dynamics. Note that our sample banks were not directly affected by the ban in the sense that very few of their positions were long credit protection. Moreover, their long positions in sovereign debt would have meant that any protection purchases would have been "covered" (In addition, the ban specifically exempted dealer banks). It is likewise unlikely that BaFin's preceding regulatory action directly affected the banks in our sample. It applied only to entities domiciled in Germany and exempted existing positions at the time it came into force. However, it is possible that if the ban had forced other market participants to close long positions (by selling protection), the induced price changes could have affected the trading activity of the German banks.

The estimation for the ban period finds an interesting positive coefficient on changes in sovereign CDS spreads, which is not present or weaker in earlier periods. If the ban did, in fact, induce price pressure (downwards), then the positive coefficient would imply the opposite of the hypothesized response: more selling by our banks rather than short covering. Referring to Figure 3, there is little visual evidence that our banks reduced their positions in aggregate during the period of the ban.

Table IA1: Heckman Regressions (Crisis Timeline)

	Pre-Oct09	Nov09-Feb10	Mar10-Nov10	Dec10-Aug11	Sep11-Oct12	Nov12-Aug13
DEP. VARIABLE: dif_dtcc_nba	(1)	(2)	(3)	(4)	(5)	(6)
LD.dtcc_nba	0.290***	0.283**	0.202	0.392***	0.528***	0.361
	(0.000)	(0.040)	(0.250)	(0.001)	(0.003)	(0.202)
L.logbankspread	0.146	-0.142	0.422	-0.0698	-3.76***	-4.23***
	(0.845)	(0.958)	(0.858)	(0.947)	(0.001)	(0.000)
D.logbankspread	-1.37*	-11.4**	-0.184	-0.431	-4.19**	-4.23*
	(0.067)	(0.012)	(0.894)	(0.875)	(0.034)	(0.050)
L.logsovspread	0.492	6.13	-3.57***	0.0540	0.459	-2.32
	(0.574)	(0.190)	(0.002)	(0.976)	(0.794)	(0.171)
D.logsovspread	16.7*	-3.45	-69.3	28.4	-62.5*	94.5***
	(0.090)	(0.937)	(0.283)	(0.383)	(0.060)	(0.001)
L.logbankspread∗ D.logsovspread	-3.17	0.147	14.6	-6.32	12.5*	-19.1***
	(0.121)	(0.988)	(0.277)	(0.365)	(0.056)	(0.002)
D.logbankspread∗ D.logsovspread	3.72**	-4.41	-2.00	3.55	2.21	-39.8*
	(0.020)	(0.865)	(0.832)	(0.522)	(0.520)	(0.077)
L.regcapratio	35.6	117.7*	-21.8	106.0	329.3***	38.0
	(0.210)	(0.067)	(0.608)	(0.109)	(0.002)	(0.352)
L.rwaratio	-11.1***	28.1	-18.8**	-14.6	-50.9**	-20.5***
	(0.000)	(0.286)	(0.017)	(0.423)	(0.022)	(0.006)
L.logsovspread∗ L.regcapratio	-8.65	-16.0	4.66	-25.3**	-46.0***	-5.07
	(0.152)	(0.190)	(0.555)	(0.034)	(0.006)	(0.505)
L.logsovspread∗ L.rwaratio	1.05	-4.80	4.22***	5.12*	8.68**	5.44***
	(0.111)	(0.392)	(0.010)	(0.085)	(0.025)	(0.001)
L.depov_nba	-21.2***	-2.36	0.880	4.05	-4.34	9.49
	(0.001)	(0.742)	(0.851)	(0.663)	(0.554)	(0.215)
LD.sovpos	-44.0	88.3	-32.2	48.8	12.9	-34.4
	(0.379)	(0.521)	(0.259)	(0.594)	(0.690)	(0.337)
bond-CDS basis	-0.000535	-0.0000657	-0.00152	0.000578	0.000652*	-0.00434*
	(0.597)	(0.977)	(0.417)	(0.780)	(0.076)	(0.080)
Constant	3.13	-36.2*	14.0	-4.85	10.3	24.5***
	(0.542)	(0.056)	(0.286)	(0.576)	(0.310)	(0.009)
Observations	6,259	868	2,426	2,463	3,728	2,554

This table presents the estimates of the Heckman regressions split into six time intervals. All columns (1-6) refer to the second-stage main regression results scaled by non-bank assets. All variables are defined as in Table 4. The independent variables "L.logbankspread", "D.logbankspread", "L.logsovspread", "D.logsovspread", "banklevel_sovdiffs", "bankdiffs_sovdiffs", "L.regcapratio", "L.rwaratio", "sovlevel_regcap", "sovlevel_rwaratio", "L.depov_nba", "bond-CDS basis" and the regression constant are presented in e-04, whereas the independent variable "LD.sovpos" is presented in e-15. All errors are robust clustered at the bank-country pair level. ***, **, * denote statistical significances at 99%, 95% and 90% levels. P-values are in parentheses.