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

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Abstract:

Using a comprehensive data set from German banks, we document the usage of sovereign credit default swaps (CDS) during 2008-2013. Banks used the sovereign CDS market to *extend*, rather than hedge, their long exposures to government default risk during the crisis period: Less loan exposure to sovereign risk is associated with more protection selling in CDS, the effect being weaker when sovereign risk is high. Somewhat surprisingly, bank risk variables are not associated with protection selling. The findings are driven by the actions of a few non-dealer banks, which sold aggressively at the onset of the crisis and started covering their positions at its height. The results suggest that the increasing shift by bank loan books towards sovereign bonds and loans over the course of the crisis caused reductions to their sovereign CDS exposure.

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1. Introduction

Nearly two decades after the creation of credit derivatives and following two major western financial crises, there is still little consensus on whether these instruments are beneficial or not for the stability of the financial sector. In the midst of the recent European debt crisis, European Union (EU) regulators undertook drastic steps[1] to curtail the use of ordinary single name credit default swaps 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 or analysis about how sovereign credit default swaps (SovCDS) was 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 European crisis. We analyse the evolution of the SovCDS positions of the entire German banking sector from January 2008 to June 2013. Our data allows us to see each German bank's individual CDS position on each country. This enables us to offer a detailed look at how individual banks managed their CDS positions and sovereign risk during the European 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, to extend sovereign risk exposure or to hedge it, and how did this usage interact with their primary exposure to sovereign risk during this episode?

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[1] After German Federal Financial Supervisory Authority (BaFin) prohibited naked buying of CDSs based on euro-denominated government bonds on May 19, 2010, the European Parliament passed the ban on same naked CDS on December 1, 2011 to hold Europe-wide. The relevant regulation took effect November 1, 2012, and remains in effect as of this writing. Duffie (2010a, 2010b) argues that there was little reason to ban short speculation in government bond markets.

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

[Insert Figure 1 here]

The figure shows the dates of two key peaks of stress in the sample, corresponding to developments in Greece, as well as the most salient event ending the crisis, the announcement of effectively unlimited intervention by the Governor of the ECB, Mario Draghi.

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. But there is also important heterogeneity among banks. The figure shows the overall stronger credit (lower spread) for the 3 large global banks designated as dealers, as well as the weaker non-dealers. The latter group includes one bank, IKB, that actually did require bailouts by the German state during 2008. The data in our study thus offers unprecedented variation in credit risk both in time-series and cross-sectionally, both for the entities referenced in the contracts and for the actors who are trading them.

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

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[Insert 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), and Parlour and Winton (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 the hedging should be expected to scale with the quantity and degree of the risk exposure.

Empirical evidence on bank use of corporate credit derivatives reports evidence on different scales of hedging by banks. Gündüz, Ongena, Tümer-Alkan, and Yu (2016) document that extant credit relationships of German banks with riskier corporate borrowers increase banks' CDS trading and hedging of these exposures, whereas Gündüz (2016) 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 the aggregate amount of such transfer is negligible.[3]

To our knowledge, no theoretical models or empirical studies have specifically spoken to the issue of credit risk transfer when 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

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[3] Other empirical studies of bank use of credit derivatives include Hirtle (2009), Norden, Buston, and Wagner (2014), Mayordomo, Rodriguez-Moreno, and Peña (2014), Shan, Tang and Yan(2014), Begenau, Piazzesi, and Schneider (2015), and Hasan and Wu (2015a, 2015b).

(2015), Becker and Ivashina (2014), and Crosignani (2015), banks absorbed an increasingly large fraction of this debt as the crisis went on. On the one hand, if hedging were ever to be desirable, this would seemingly be the setting. On the other hand, to the extent that hedging or risk transfer of corporate loans is motivated by the desire to free up balance sheet capacity, this motivation is not present for sovereign exposure, which carries zero capital charge for banks in our setting.

In this context, the first-order finding of this paper is remarkable: German banks 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 hedging of long sovereign bond positions by purchasing CDS protection only 10.5% of the times such bond positions are held, whereas we see the opposite – selling protection and holding long bond positions simultaneously – four times as often. Not only were the incentives to hedge not present, it appears at first glance as if they 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); Crosignani (2015); Acharya, Mehran and Thakor (2016)) suggest that incentives to extend risk exposure could be greatest for banks with weaker capital positions or higher 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 by particularly by undercapitalized Euro-zone 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 for 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 is not driving the use of sovereign CDS. In 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 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 excess risk-taking (e.g., Myers and Rajan (1998), Calomiris and Jaremski (2016)).

Our strongest finding is a significant negative association between SovCDS trade 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 (Tier 1 capital) that 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 relatively higher risky sovereign loan exposure (which nevertheless carries zero weight), where a bank with higher RWA has more commercial loan exposure (which carries a high weight).

Under this interpretation, our results point to a *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 bank sector (or correlated risk taking), but with some banks choosing to implement this position via derivatives. Although sovereign bonds and derivatives on EU countries have the same zero risk-weight privilege and therefore treated the same for regulatory capital purposes, cash bond positions require financing (via the repo market) which CDS do not.[4] In addition, CDS positions remain off balance sheet, which some banks could prefer.

We see the substitution effect across time, as well as across banks. Banks overall increased their primary exposure to sovereign risk over the course of the crisis, and this is reflected in an attenuation in net short CDS exposure after 2010. The effect is, however, attenuated or even reversed for high levels of sovereign risk. Banks with low loan exposure who sold protection most aggressively tended to buy back protection referencing the states that became extremely distressed. This is consistent with position risk management, perhaps being triggered by loss levels or value-at-risk limits following the rise in sovCDS and market volatility after 2010.

Finally, these results are driven by the activity of non-dealer banks. Dealers, by contrast, sell less protection overall and do not exhibit the same substitution effect. In fact, among the non-dealers most of the sovereign CDS risk is borne by just three institutions making extremely aggressive bets at the start of the crisis and covering their positions at its height.

In summary, this paper provides an in-depth look at the forces driving the evolution of banks' SovCDS positions during a sovereign debt crisis. German banks responded to the crisis by using credit derivatives to take on more, not less, risk through these derivatives. We provide new evidence on factors that are and are not driving this risk taking. Our results imply that a full understanding of the bank-

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4 However short CDS positions would be subject to collateralization.

sovereign risk dynamic in the crisis requires incorporating SovCDS into the complete picture.

The outline of the paper is as follows. In the next section we describe in more detail our data. Section 3 describes our empirical methodology. Section 4 presents results of our estimation that attempt to explain changes in banks' SovCDS positions. Section 5 provides some subsample evidence. An extended set of positions on exposure sovereign risk for further countries is examined in Section 6. A final section summarizes and concludes.

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), in particular, 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 of bought and sold positions on each reference entity for each financial institution.[5] 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,[6] our sample is comprised of all 16 banks active in the CDS market and is therefore

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[5] See DTCC(2009) on global coverage. Notice that our regulatory access to DTCC positions enables us to see each banks' position on each sovereign, which is highly granular than the studies with only website access to DTCC aggregate positions, i.e. Oehmke and Zawadowski (2016), or Augustin, Sokolovski and Subrahmanyam (2016).

[6] 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, the earliest possible start for a reliable time series is therefore January 2008.

inclined towards larger players in the German banking system.[7] For each sovereign-bank pair, 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.

Bank regulatory ratios, are retrieved from the Deutsche Bundesbank's Prudential Database (BAKIS).[8] Other bank-specific information, such as 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). Sovereign bond holdings 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 state on each date, we use CDS fee on the 5-year maturity contract with CR restructuring clause denominated in US dollars as our reference price for credit protection. Other variables such as the EUR/USD exchange rate and the VSTOXX volatility index are from Bloomberg.

2.2. Descriptive characteristics of German banks through the crisis

Table 1 presents the statistics for the 16 German banks in our sample. The DTCC tags any institution "which is in the business of making markets or dealing in

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[7] 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 unions. These are smaller sized banks that mostly target local deposit and loan businesses and typically are not active in OTC derivatives markets.

[8] See Memmel, C and Stein, I (2008), "The Deutsche Bundesbank's Prudential Database (BAKIS)", Schmollers Jahrbuch, 128, pp. 321-328.

credit derivative products" as a CDS "dealer",[9] and three of our sample banks fall into this category (Deutsche Bank AG, Commerzbank AG, and Unicredit). Because they play a different role in the CDS market, our analysis will include separate examination of dealers and non-dealer positions.

[Insert Table 1 here]

German banks had an average weekly CDS price of 162 bps during the interval of 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 are positive over our sample period as credit risk across EU states deteriorated.

Our main measure of bank size is total loans and advances to non-banks. 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 will play an important role in our analysis. We define two relevant metrics based on each banks reported "risk-weighted assets", which is a standard regulatory calculation that applies fixed risk weights to each category of bank asset (with higher weighting denoting supposedly more risk). The RWA ratio is calculated as the risk-weighted assets divided by NBA, and the Tier 1 ratio is calculated as the quarterly core capital (common book equity plus retained earnings)

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9 http://www.dtcc.com/~/media/Files/Downloads/Settlement-Asset-Services/DerivSERV/tiw_data_explanation.pdf. The DTCC tags the G14 dealers naturally as "dealer" as well: 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.

divided by risk-weighted assets. Unconditionally, dealers and non-dealers do not differ much on either dimension.

To gauge flight-to-quality effects, we will also be interested in deposit flows for German banks. For this purpose, 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 in the sample period.) The last two rows in Table 1 show that this source of funds is on average much larger for dealers than non-dealers in both 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 states over the observation period.[10] In an attempt to utilize the sovereign states whose CDS are most actively traded, we identified the 20 European states whose banks are considered for the stress tests conducted by the European Banking Authority (EBA) starting in 2009. Some of our analysis will separately consider 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.[11]

[Insert Table 2 here]

The main 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

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[10] Siriwardane (2015) shows that the US CDS market is also very concentrated and dominated by a handful of buyers and sellers. Gündüz, Ongena, Tumer-Alkan and Yu (2016) make use of 14-17 German banks that actively trade in the CDS market. By including non-bank financial institutions, Gunduz (2016) carries out an analysis of 25 active German parties that trade CDS.

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

following analysis. This weekly snapshot of the bought and sold CDS position of the bank 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 the statistics in Panel A of Table 2 indicate that the German banks are net sellers of sovereign CDS within the 2008-13 intervals. This finding is remarkable because it immediately rules out a primary hypothesis 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.)

Our empirical analysis will attempt to shed light on the factors driving bank selling. We use as our primary measure the monthly difference of the net CDS position, which reveals the trading activity in one month. Its average value is near zero (-0.69 EUR million), however with a standard deviation of 41 EUR million. The dealer banks' highly fluctuating trading activity can be observed from the standard deviation of 67 EUR million, well exceeding that of 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 bank-specific, and (ii) total sovereign debt from Eurostat, which is a country-specific variable.

An important consideration in our analysis is the decision to make use of null entries, i.e. whenever the CDS position is zero, indicating no trading activity of the bank on the specific sovereign. The next section will discuss how we make use econometrically of the information from both the null observations and net values. However, Table 2 also provides the statistics of the weekly positions without the inclusion of null values. The average of weekly net CDS positions for all banks jumps to -177 EUR million when zero positions are not considered. Moreover, the standard deviation of the 13 non-dealers (545 EUR million) now exceed those of the three dealers (440 EUR million), which shows that dropping the inactive bank-state

positions leads to a remaining set of observations with high volumes for the non-dealers.

In addition, the Panel B in Table 2 shows the value for sovereign CDS prices averaged over all states and weeks. The average sovereign CDS price is 210 bps with a high variation of 619 bps, mostly due to the sovereign credit risk problems of several troubled European economies. Similar to 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 state, which we have at monthly frequency. 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 sovereign risk in these primary securities. Of all the bank-state-month observations in our sample, long positions were held 71% and short positions were held only 5% of these observations. Averaging across all observations excluding those for German government bonds gives a position size of 231 million Euros in bond value. Multiplying by 19 (the number of states excluding Germany) gives an average bank-month exposure to sovereign debt of 4.4 billion Euros. Multiplying by 16 (the number of banks) gives an average exposure of the banking system of 70 billion Euros 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

and is positive in only 10.5%. We 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 billion Euros, the total exposure to sovereign risk was economically large. For comparison, the total Tier 1 capital of our 16 banks was approximately 200 billion Euros 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 percent in January 2010.[12] Over the course of the sample, banks closed their protection selling position by almost half as of mid-2013.

A closer look at the positions reveals that three of the bank positions account for almost three-quarters of overall protection selling position in the market during peak times in 2010 reaching a value over 30 billion Euros (Figure 3B). This value is reached when three largest sell positions are aggregated on each date separately. In 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 sell positions in Figure 3B are revealed to be almost fully belonging to three specific non-dealers in Figure 3C. The three dealers in our sample also are net protection sellers; however, the three main protection selling non-dealers have an aggregate magnitude above 30 billion Euros in 2010, well beyond that of dealers. The magnitude of the "big three" non-dealer's short position reaches 30 billion Euros at the start of 2010. For

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12 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 percent of each banks own assets.

comparison, their total assets (NBA) at the end of 2009 were 326 billion euros and their total Tier 1 capital was 28 billion euros.

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

[Insert 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 trade activity within the month. This will be our main dependent 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 will enable 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 dominant 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 might be seem to be explained by a number of macroeconomic variables, our study has the ability to utilize both cross-bank and cross-sovereign variation to discriminate against a number of hypotheses. We 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 raise 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 banks were not using SovCDS for hedging the primary exposure of their bond positions in aggregate, our data does allow us to examine their trading in the context of the full exposure to each country. We would expect banks to manage both instruments simultaneously. Because our specification is in differences, we use the change in each bank's bond position in each state

(*LD.sovbonds*). Since we are viewing CDS positions as exogenous, we lag this variable by one period.

b) Sovereign risk

Past month's log CDS spread of the sovereign (*L.logsovspread*) will be 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*) will show whether banks position themselves in the sovereign CDS market dynamically in response to the changes of default risk of the underlying sovereign reference entity.

c) Bank risk

We use past month's log CDS spread of the bank (*L.logbankspread*) in order to understand how banks that have a higher default risk undertake positions in the sovereign CDS market. As an alternative to 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 risks

We are interested whether banks that have a higher default risk take positions according to changes in the default risk of the sovereign as well. In order to identify this we interact past month's log CDS bank spread with the contemporaneous changes of the log CDS sovereign spread (*banklevel_sovdiffs*). Similarly, we interact contemporaneous changes of the log CDS bank and sovereign spreads (*bankdiffs_sovdiffs*).

e) Regulatory ratios

Bank regulatory ratios are core to our analysis. In order to conform to, and potentially "arbitrage" the regulatory capital requirements, banks undertake asset management activities that also include sovereign risk taking. We use Tier1 Ratio of the bank so as 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 risk-weighted assets (RWA) of the bank. We use the quarterly lagged value for our month-level analysis (*L.regcapratio*). By using past quarters' regulatory ratio, we ensure that the bank's monthly CDS trading activity happens after the quarterly reporting of accounting ratios.

The ratio of risky assets based on Basel risk weights is also (from the perspective of regulatory capital adequacy) relevant in order to observe whether banks that possess a riskier balance sheet further take on or lay 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 lagged with respect to the CDS trading activity as well (*L.rwaratio*).

f) Interactions with regulatory ratios

The interactions of both regulatory ratios with past month's log sovereign CDS are also important to identify if 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 (*sovlevel_regcap* and *sovlevel_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 at monthly frequency.

3.2. Specification

Because CDS positions of individual banks in individual countries are highly nonstationary, our dependent variable is in first differences. Our overall econometric design is thus 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, for low frequency bank balance sheet and regulatory variables, lagged levels are also employed.

As already noted, a consequence of first-differencing is that most observations of the dependent variable are zero. Since banks do not change CDS positions in all sovereign names frequently, we apply a Heckman (1979) selection analysis in order to disentangle the likelihood that banks change sovereign CDS positions from how much they trade conditional on the choice to trade. Idle inventories that entail null changes may reveal information on the risk-taking activity, along a separate dimension from information about the trade quantity. For instance, null change in a

net short CDS position when underlying risk has increased could reveal an active strategy not to reduce the short exposure to contain risk.

Econometrically, combining the trading activity decision with how much it trades might be misspecified and lead to biased estimates if related economic incentives are driving the two decisions. It is thus important to attempt to identify separate drivers of variation in each stage.

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 contemporaneous 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 (from month *t* to *t+1*) change in bank *i*'s net CDS positions on sovereign *s*:

$dif\_dtcc_{i,s,(t+1)-t} = \beta_0 + \beta_1 dif\_dtcc_{i,s,t-(t-1)} + \beta_2 logbankspread_{i,t} + \beta_3 logsovspread_{s,t} +$

$\beta_4 logbankspread_{i,(t+1)-t} + \beta_5 logsovspread_{s,(t+1)-t} + \beta_6(logbankspread_{i,t} *$

$logsovspread_{s,(t+1)-t}) + \beta_7(logbankspread_{i,(t+1)-t} * logsovspread_{s,(t+1)-t}) +$

$\beta_8 regcapratio_{i,t} + \beta_9 RWAratio_{i,t} + \beta_{10}(logsovspread_{s,t} * regcapratio_{i,t}) +$

$\beta_{11}(logsovspread_{s,t} * RWAratio_{i,t}) + \beta_{12}\frac{depov_{i,t}}{nba_{i,t}} + \beta_{13} sovbonds_{i,s,t-(t-1)} + u_{i,s,t}^{(1)}$ (1)

And the first stage selection equation is:

$$Z_{i,s,t} = \gamma_0 + \gamma_1 dealer_i + \gamma_2 absdif\_sov_{s,t} + \gamma_3 lagdiff\_ind_{i,s.t} + \gamma_4 posdtcc\_ind_{i,s,t} + u^{(2)}_{i,s,t}$$

$$trade_{i,s,t} = 1_{\{Z_{i,s,t}>0\}} \tag{2}$$

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

We also estimate the model replacing unscaled monthly changes with the bank-level scaled (by non-bank assets) and sovereign-level scaled (by sovereign debt) variants to control for size effects.

4. Empirical Results

4.1. Baseline Results

Table 3 presents the baseline set of results with the Heckman selection analysis. Odd-numbered columns report the estimates of main equation (1). These condition upon the first-stage (equation (2)), whose estimates can be found in even-numbered columns.[13]

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.

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13 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: $\operatorname{atanh}\rho = \frac{1}{2}ln\left(\frac{1+\rho}{1-\rho}\right)$. The log transformed standard error of the residual in the first equation is reported in our baseline table as $lnsigma$ as well.

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 current month's trading activity. The absolute value of the contemporaneous change in the sovereign CDS spread is positively related to having any trading activity; however is not statistically significant.

The second-stage analysis shows our main positive result that sovereign CDS spreads, the risk-weighted assets ratio, the interaction of the two have a significant effect on banks' sovereign CDS trading activity in all three specifications. The next subsection will consider the interpretation of these effects in detail. For the moment we note the signs of the three coefficient estimates. The two marginal effects are each negative, while the interaction effect is positive. Naively, this would 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 having an average RWA ratio (or higher), the sign of the $sovspread$ effect is positive. The marginal $RWAratio$ effect is indeed negative – except when the level of sovereign risk is very high.

[Insert Table 3 here]

The positive marginal country risk effect shows the econometric benefits of our data panel. 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.

Another interesting finding is the significant (in two of the three versions) negative coefficient 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 unscaled specification implies that when summed across the 20 states, 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 million Euros per month or 1.3 billion Euros per year.[14]

The findings in Table 3 are notable also for an absence of evidence supporting some other hypotheses to explain 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 banks' own riskiness. This suggests that the mechanisms driving the risk-shifting through purchase of risky government bonds by riskier banks as identified by Acharya and Steffen (2015) do not extend to credit derivatives.

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 risk, which this result affirms. Hedging would show up here via 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

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14 The cross-bank standard deviation of monthly changes in total CDS positions is 423 million Euros.

effects may be at work for different banks, or the specification (i.e., using lagged differences) may lack power to detect either one. We will argue below that our RWA ratio variable does allow us to indirectly capture (in levels) the banks' total sovereign exposure.

Despite these negative results, overall our specification is does succeed in explaining an economically significant fraction of the aggregate pattern of CDS protection selling observed in the sample. We can quantity 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:

$$\widehat{yexp}_{i,s,t} = E\big(y_{i,s,t}\big|y_{i,s,t}\ observed\big) * \Pr\big(y_{i,s,t}\ observed\big). \qquad (3)$$

Figure 4 shows the fit over the course of the sample by aggregating these values in each month across banks and sovereigns $\big(\sum_{i,s}\widehat{yexp}_{i,s,t}\big),$ 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 inititial sustained selling phase, followed by a gradual covering of short positions. The fitted model accounts for 12.5 percent of the variation in the aggregate cumulated series.

[Insert Figure 4 here]

How much of the explanatory power in the time-series is coming from the selection equation and how much is coming 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 5A) and the first-stage probit (Figure 5B).The second-stage

contribution comes from the expected value of the dependent variable, conditional on the dependent variable being observed, that is;

$$\widehat{ycond}_{i,s,t} = E\big(y_{i,s,t}\big|y_{i,s,t}\ observed\big) \qquad (4)$$

and as $\widehat{ycond}_{i,s,t}$ is aggregated across banks and sovereigns in a given month, the time series for Figure 5A is $\big(\sum_{i,s}\widehat{ycond}_{i,s,t}\big)$. The selection probability for each bank i, sovereign s, at month t is;

$$\widehat{yexp}_{i,s,t}/\widehat{ycond}_{i,s,t} \qquad (5)$$

which constitutes the time series in Figure 5B after averaging across bank and sovereigns.

The main effect of the selection equation is a dampening of the expected activity over time. In Figure 5B, 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 a main driver of position adjustments is having positions (*posdtcc_ind*), and our sample banks closed out most of their positions over the period (see Figure 3).

However the main explanatory power comes from the second stage. Quantitatively, the fraction of the variance in the second-stage anaylsis 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%.

[Insert Figure 5 here]

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 point us primarily 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 6A 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 states (and multiplied by the monthly conditional trade probability) as a dashed line. The fitted terms capture most of the time trend as well as a notable degree of the variation. The variance of the fitted series is 20% of the variance of the observation series. Also shown (dotted line) is the negligible net contribution of the sovereign risk term.

Figure 6B 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.

[Insert Figure 6 here]

How should one interpret the risk-weighted assets ratio in our specifications, given that the regressions control explicitly for two conventional and direct measures of bank risk, 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 the loan book. That is, two banks having the same level of lending (i.e., non-bank assets, which is the denominator, and which includes sovereign loans) and having

the same Tier 1 capital and the same credit spread, must differ in the RWA primarily because one has a lot of sovereign risk and the other has more commercial risk. Note that, in computing RWA, EU rules permit zero weights to be assigned to bonds, loans, *and CDS* exposure to sovereign risk of member states, regardless of the actual level of risk of those assets. Thus, controlling for risk, lower RWA should be interpreted as indicative of a higher sovereign exposure.

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 positions objectives, perhaps because of the former stay off balance sheet.

Turning to the interaction effect, 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 the sign of the interaction effect is positive.) The magnitude of the estimated coefficients tell us that the marginal impact of the RWA ratio on changes in CDS positions effectively vanishes high levels of sovereign risk (i.e., over 400 basis points), and even reverses for extremely high levels. This is consistent with the same banks that initially sold the most protection (the ones with high *RWA* ratios) tending to cover those positions at the height of the crisis. From Figure 6A, we can see that the same effect occurs during the height of the US turmoil in late 2008 and 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 (2014) and Crosignani (2015), 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 trend down in the RWA ratio that is exhibited in our sample. (And note that this trend does not coincide with a trend down in bank risk as measured by CDS spreads until after January 2012 (See Figure 2). Thus, it appears 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.

4.2.1 Robustness on Time Buckets

As robustness we divided our sample into two sub-periods (January 2008 – November 2010 and December 2010 – August 2013). The cut-off period encompasses the peak of the European debt crisis when Ireland was bailed out in November 2010 by the EU and the IMF. Table 4 presents that our main finding on the RWA effect is highly significant in the first January 2008 – November 2010 subsample, whereas not prevalent in the second subsample. These are consistent with the above discussed risk-extension behaviour of banks in the early crisis period, followed by covering of the short sovCDS positions as the sovereign debt crisis deepened.

[Insert Table 4 here]

4.2.2 Robustness on Outlier Effects

The results in Table 3 are also robust to any outlier effects; for instance removing a bank (West LB) whose 85 billion toxic assets were transferred in November 2009 to create Germany's first "bad bank" in an attempt to cure the financial institution and prevent systemic effects. Table 5 presents the results that are even stronger without WestLB.

[Insert Table 5 here]

5. Subsample Analysis

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

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 was as non-dealer banks. From Figure 3, we know that both types of banks were net protection sellers during the sample. It is quite plausible however that the factors leading them to do so were distinct.

Table 6 presents estimations for our specification for estimated separately for these two types of institution. Results for dealer are shown in columns (1) - (6). Columns (7) - (12) give the non-dealer results. Even-numbered columns provide the results for the first stage, whereas odd columns present the second-stage results, as before. Perhaps surprisingly, we do not see strong differences between the banks in

the first stage (apart from a less negative constant term for dealers, capturing their higher volume of trade), indicating similar motivations drive the decision to trade.

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 affect non-dealers.

In contrast, dealer banks having safer (higher) Tier 1 regulatory ratio 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 ones. In particular, dealers sold more aggressively after 2010 when the deposit inflows occurred, but at a point where non-dealer 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 3. 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 negative coefficient on lagged changes in sovereign bond positions for non-dealers. This is consistent with complementary use of derivatives and bonds to achieve desired country risk allocations by these players. (This contrasts with the bank level substitutability

implied by the RWA effect.) For dealers, the point estimates on bond position changes are positive (although insignificant) consistent with hedging, illustrating an interesting difference across institutions.

[Insert Table 6 here]

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 3 found no significant role for either levels or difference in country risk in explaining position changes.[15] To investigate this seeming inconsistency further, Table 7 presents the estimations results when the sample is broken down into CDS positions on GIIPS (columns (1) - (6)) and non-GIIPS (columns (7) - (12)) states.

Comparing the respective second-stage estimates across respective columns, a first observation is that the economically large RWA effect and its interaction with 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. But the magnitudes for the non-GIIPS sample are not much diminished from their full-sample values in Table 3. (The 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:

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

27.9% for the GIIPS sample versus 14.9% for the rest of the EU. 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 states.

The table also indicates a significantly more negative effect of deposit flows on selling of GIIPS sovCDS. We have already seen that the deposit inflows to dealers after 2010 appears related to their protection selling in this period. We now see those flows linked to selling of risky countries in particular. However, this sheds little light on the predominance of these countries in the selling activity of non-dealers.

[Insert Table 7 here]

Finally, Table 8 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 6) or for all banks in the GIIPS countries (Table 7). 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.

[Insert Table 8 here]

6. Evidence from other Sovereign CDS

Are the patterns of sovereign protection selling that we have documented driven by the particular circumstances of the Euro-zone crisis? We can begin to address this question by extending our sample cross-sectionally. In this section we employ the CDS positions of an extended set of countries that are not used in the baseline sample. We add eight non-EU countries that did not have a representative bank in the EU-wide stress tests, thus could be thought to be affected from the bank-sovereign credit risk nexus to a lesser degree during the crisis. Moreover, we make use of the CDS positions on five major developed market countries, and six emerging market countries.[16] We would like to see whether the results in the last section remain similar, or are primarily confined to GIIPS economies.

We aggregate the exposure of all our banks in each of the following global market segments: GIIPS countries, non-GIIPS EU countries, emerging markets, and developed markets. Figure 7A presents the time series of the average exposure per country in each of these segments. We observe once again that the highest protection selling exposure is on an average GIIPS country which reaches 4 EUR billion in early 2010. This aggregate open net exposure on a GIIPS country has an overwhelmingly higher value than an average non-GIIPS EU country, a developed market country, or an emerging market economy, which never exceed 1 EUR billion over the observation period of 2008-2013.

Figures 7B and 7C depict the figure for dealers and non-dealers separately. Although dealers are additionally active in selling protection on the emerging market

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16 The full sample consists of five GIIPS countries, Greece, Italy, Portugal, Ireland, and Spain; Rest of EU consists of 15 countries in the baseline sample; Austria, Belgium, Cyprus, Denmark, Finland, France, Germany, Great Britain, Hungary, Malta, the Netherlands, Norway, Poland, Slovenia, Sweden and eight additional EU countries: Bulgaria, Croatia, Czech Republic, Estonia, Latvia, Lithuania, Romania, Slovakia; Emerging Markets (EM) consists of Argentina, Brazil, China, Mexico, Russia, Turkey; Developed Markets (DM) consist of Canada, Japan, Korea, Switzerland, and USA.

sovereign CDS, their exposure on GIIPS countries has been always higher than any other segment after the early days of the sovereign debt crisis in 2009. The non-dealers seem to take higher protection selling positions on non-GIIPS EU countries, reaching a country average of almost 1 EUR billion in 2010, which was also always less than sovereign exposures on an average GIIPS country. Noteworthy to mention is that these non-dealers were relatively less active in position taking on developed and emerging market economies throughout the period.

[Insert Figure 7 here]

Finally, it is worth observing that, although the GIIPS short positions dominate those of the other sets of countries, it remains the case that the average positions of both dealers and nondealers was negative for all four sets during this period. In this sense, it appears that the incentives of banks to extend sovereign risk via derivatives do not appear to be confined to the crisis.

7. Conclusion

This paper reports a perhaps surprising finding on bank behaviour during the EU 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, even though they were under no obligation (implicit or explicit) to do so. Their aggregate sovereign exposure through CDS sales reached 40 billion euros 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 on credit exposures, whereas the literature on the bank-sovereign nexus shows how risk-shifting takes place through purchasing of riskier sovereign bonds by undercapitalized banks. Surprisingly, we find no economically significant effect of bank and country risk variables. Further, we find no evidence that sovereign CDS sales are linked to changes in bond positions of 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 weights privilege for EU member state 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 bank use of sovereign CDS during the sovereign debt crisis does not appear to be driven by considerations to hedge the underlying sovereign risk exposure.

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Figures and Tables

Figure 1
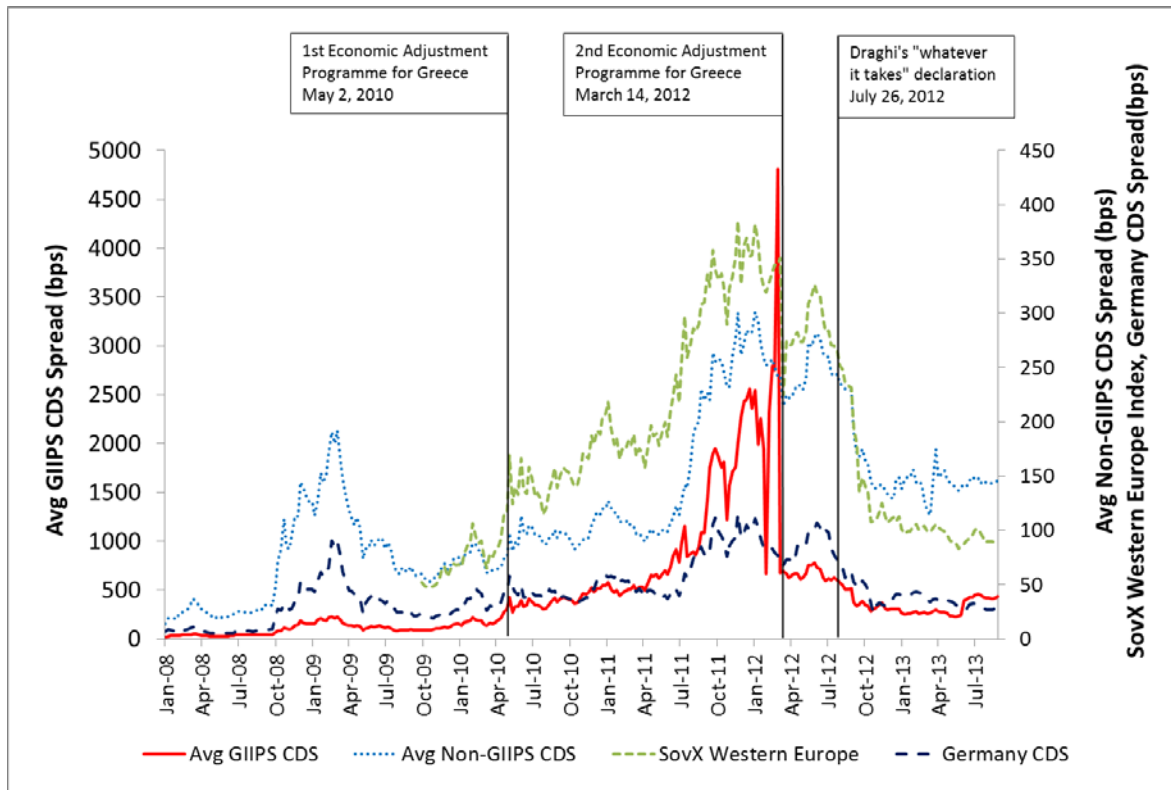
Figure 2
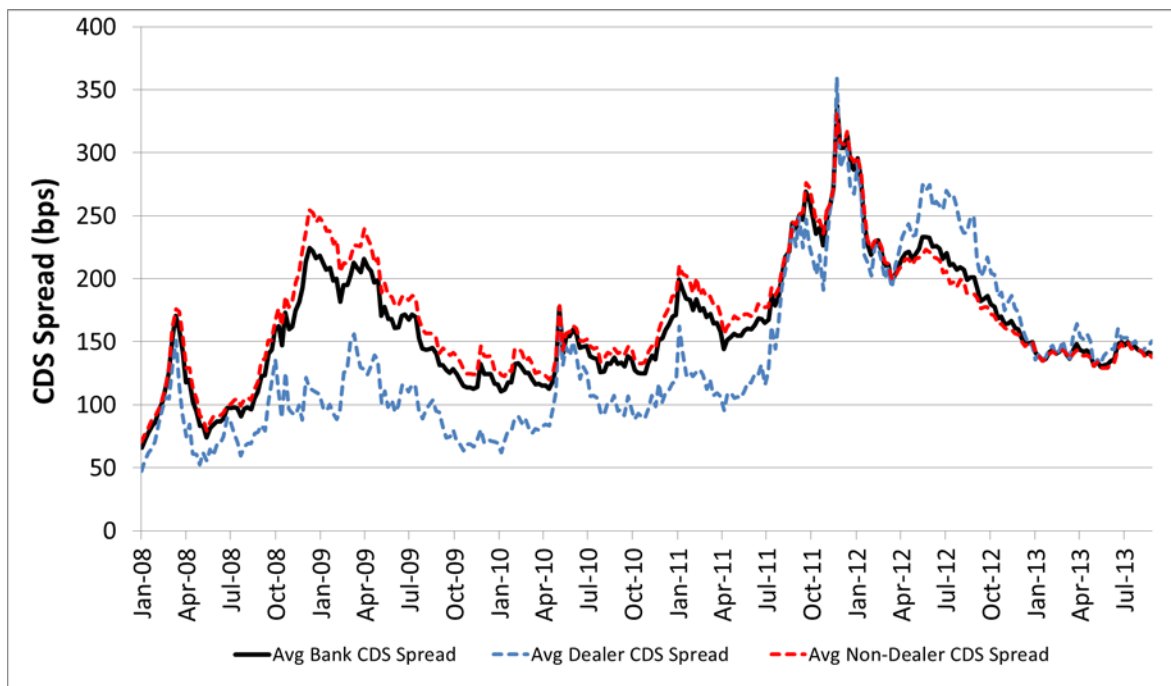
Figure 3. These figures show the position-taking of German banks in the CDS market during the sovereign debt crisis. All CDS positions are aggregated across German banks (Figure 3A), across three highest protection sellers and buyers (Figure 3B), across dealers, three highest protection selling non-dealers, and all other banks (Figures 3C and 3D). Sold positions are subtracted from bought positions, in order to reach a net aggregate exposure.

Figure 3A. Aggregate net CDS position

Figure 3B. Top 3 protection selling and purchasing positions
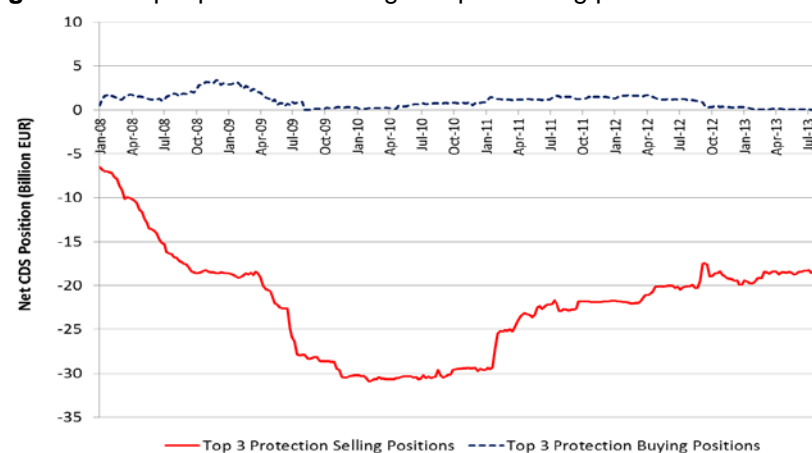
Figure 3C. Dealers vs. non-dealers
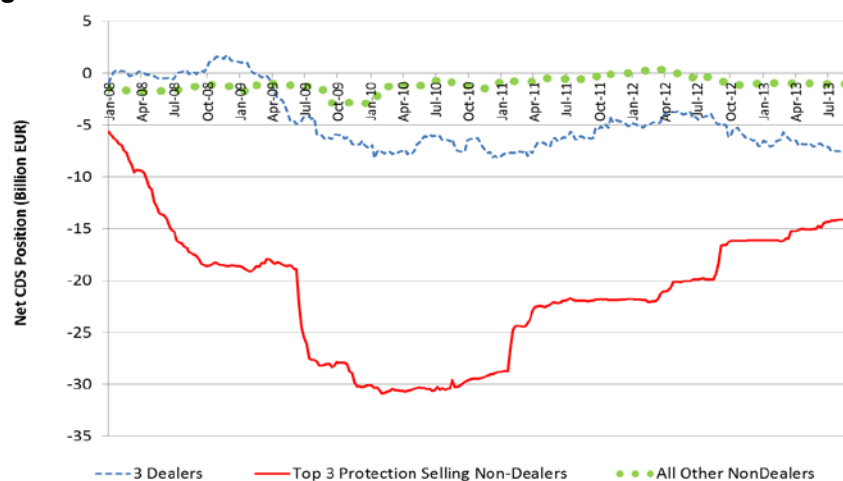
Figure 3D. Dealers vs. non-dealers (only GIIPS exposures)
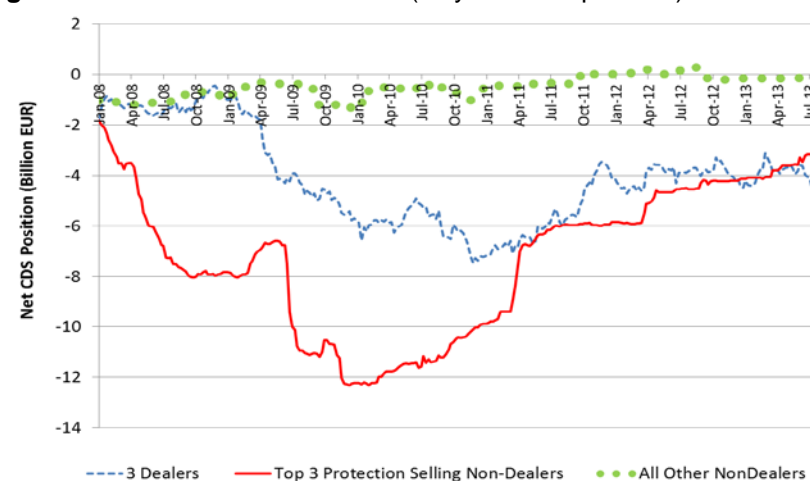
Figure 4. (Cumulated) Predicted vs. Observed Values in Heckman Analysis

This figure shows the fit of both stages of Heckman regression to the observed dependent variable (DTCC changes scaled by non-bank assets). The fitted series is computed through aggregation of $\widehat{yexp}_{i,s,t} = E\left(y_{i,s,t}\middle|y_{i,s,t}\ observed\right) * \Pr\left(y_{i,s,t}\ observed\right)$, by summing across bank-state pairs in each observation month and then cumulating the values of months starting with January 2008 (in circles, red). Observed data is aggregated by summing across bank-state pairs in each observation month, and then cumulating over months, similarly (in squares, blue).
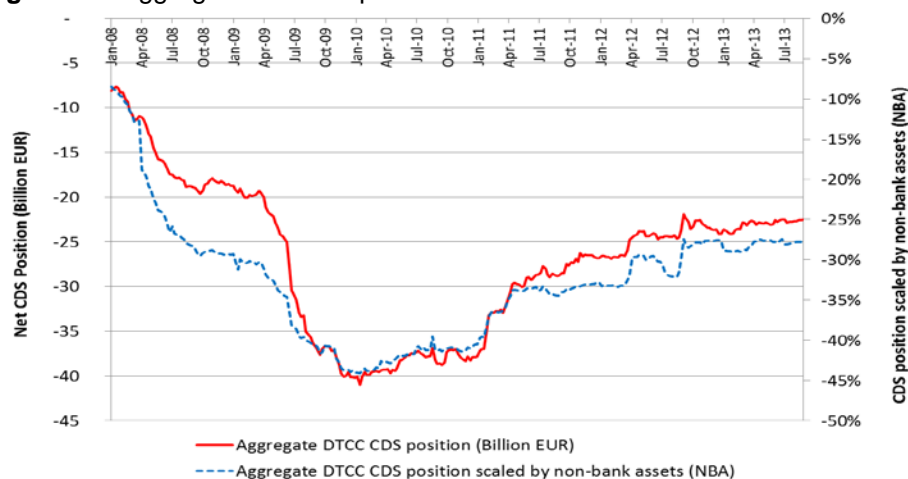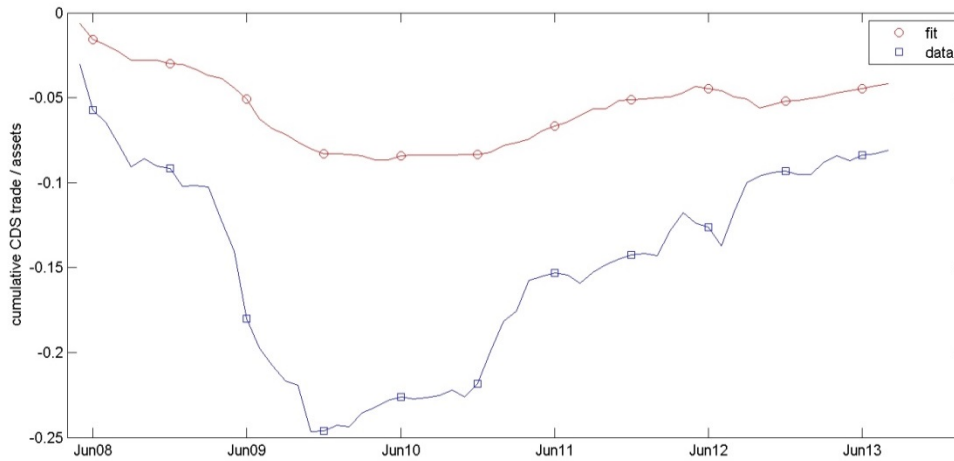

Figure 5A. Second stage of the Heckman regression

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 $\widehat{ycond}_{i,s,t} = E\left(y_{i,s,t}\middle|y_{i,s,t}\ observed\right)$. We sum across bank-state pairs in each observation month.
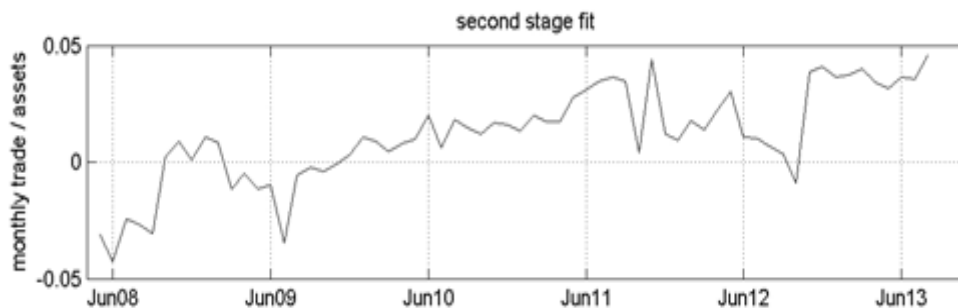
Figure 5B. First stage selection probability in Heckman regression

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 constitutes the below time series after averaging across bank and sovereigns.
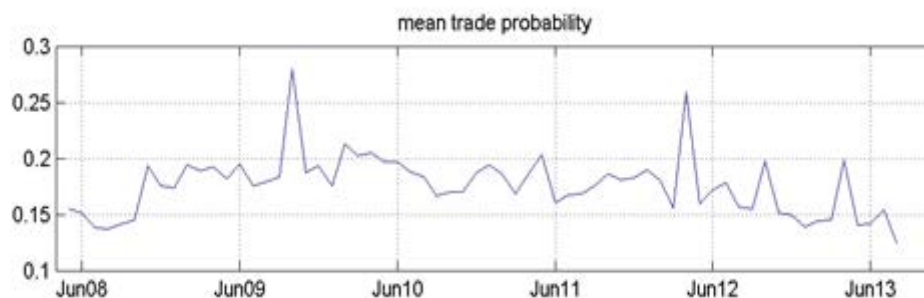
Figure 6A. Contribution of RWA Ratio to Explanatory Power in the Second-Stage

This figure shows the time series of the full sample averages of the RWA ratio variable multiplied by their second stage coefficient estimate in column (3) in Table 3 (in circles, red), and the time series of the second-stage conditional expectations $\sum_{i,s} \widehat{ycond}_{i,s,t}$ as in Figure 6B (in squares, blue).
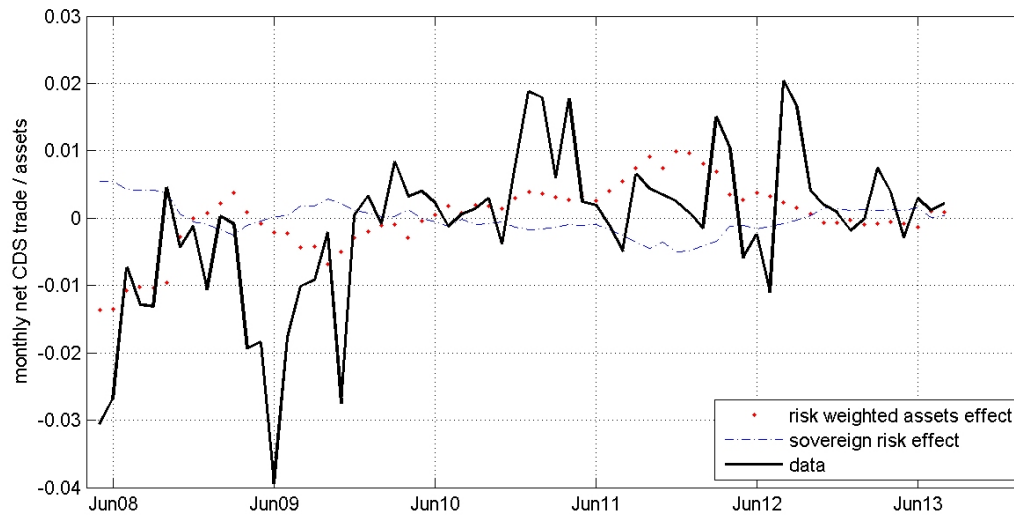
Figure 6B. Comparison of the Cumulative Contribution of the RWA Ratio Variable

This figure shows the cumulated development of the full sample averages of the RWA ratio variable multiplied by their second-stage coeffieicent estimate in column (3) in Table 3, and additionally by the average selection probability in Figure 6C (in circles, red); and the cumulative observed CDS positions scaled by non-bank assets as in Figure 5A (in triangles, blue).
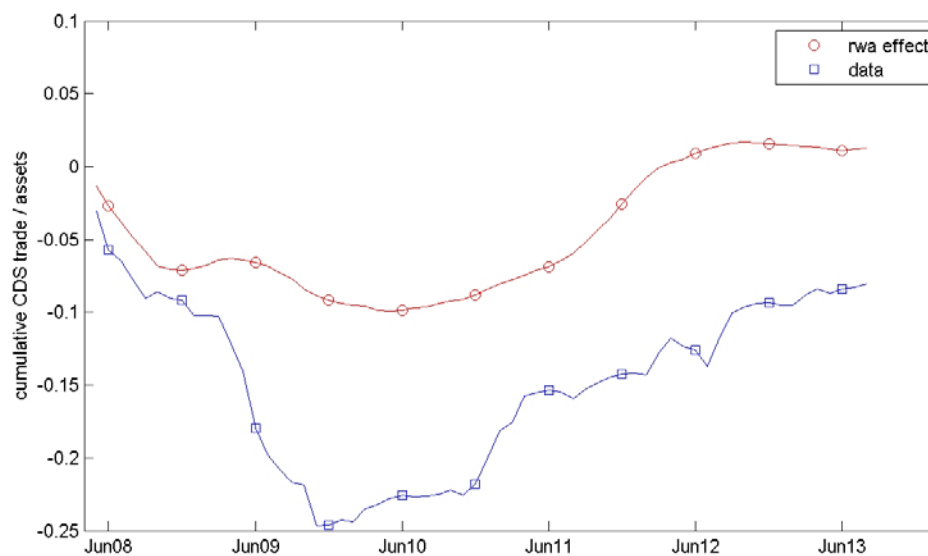
Figure 7. Analysis with Extended Set of Countries

These figures create a time series of the average exposure for a representative country in one of the four global country segments; (i) GIIPS, (ii) non-GIIPS EU (Rest of EU), (iii) Emerging Markets (EM), and (iv) Developed Markets (DM), after an initial aggregation of the net CDS position of all German banks that have exposures in that segment. Figure 7A provides the results for the full sample of German banks, whereas Figure 7B and 7C show the time series after the aggreagtion of dealers and non-dealers' positions, respectively.

Figure 7A.
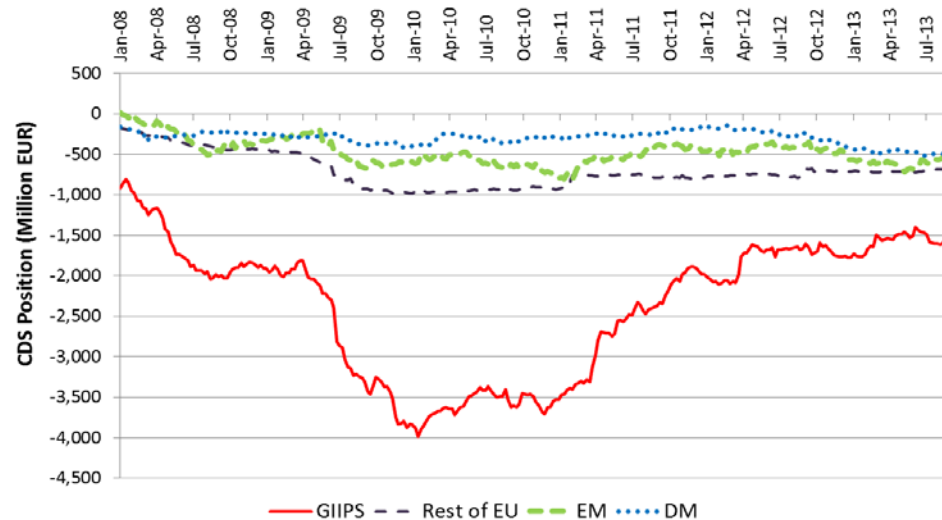
Figure 7B.

Figure 7C.

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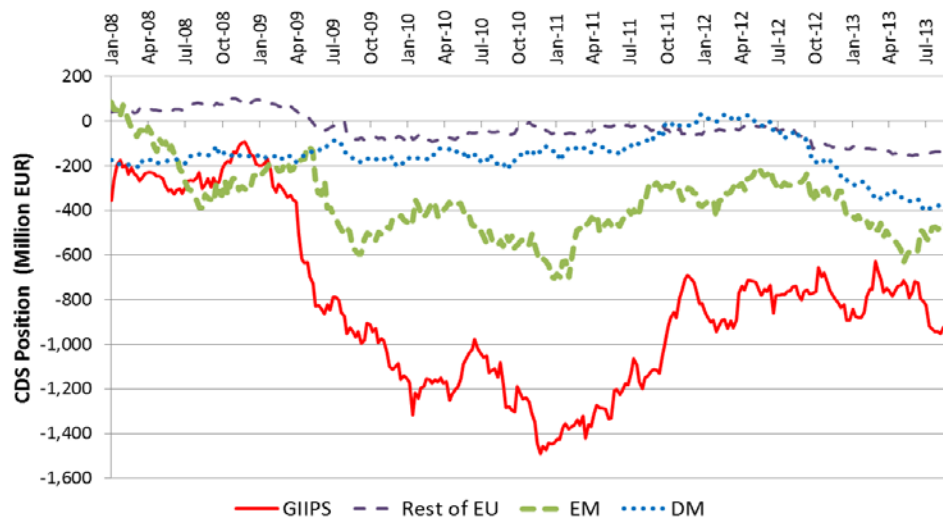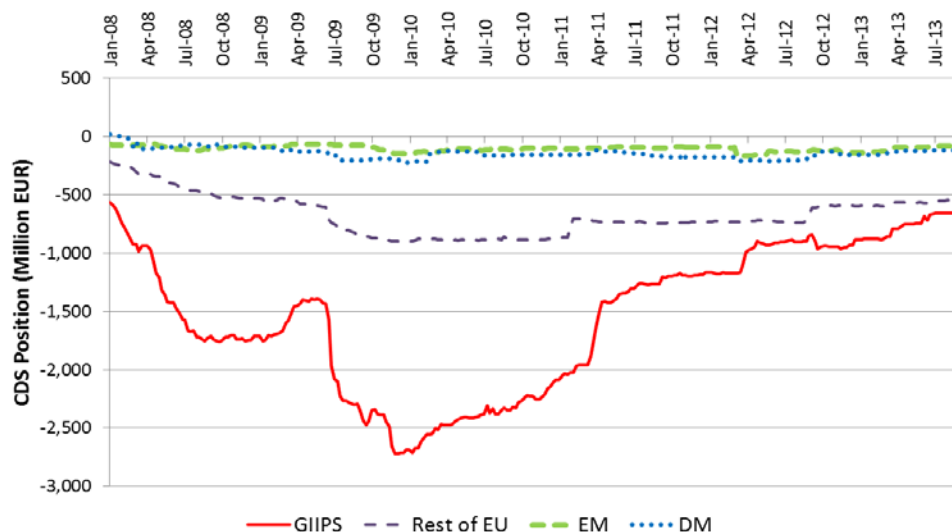
Table 1. Descriptive statistics: bank-specific variables

	Frequency	All banks		Dealers		Non-dealers	
		Mean	**Std dev**	**Mean**	**Std dev**	**Mean**	**Std dev**
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 (%)[17]	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).

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[17] 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 holdings, bond holdings, and sovereign variables

	Frequency	All banks		Dealers		Non-dealers	
		Mean	Std dev	Mean	Std dev	Mean	Std dev
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 states 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 state is retrieved from Eurostat. "without zero positions" assumes 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. Heckman regressions (Baseline Results)

VARIABLES	(1) dif_dtcc	(2) select	(3) dif_dtcc_nba	(4) select	(5) dif_dtcc_debt	(6) select
LD.dtcc	0.186***					
	(0.000)					
LD.dtcc_nba			0.356***			
			(0.000)			
LD.dtcc_debt					0.042	
					(0.215)	
L.logbankspread	0.441		-0.307		0.0093	
	(0.301)		(0.640)		(0.971)	
D.logbankspread	-0.104		-0.734		-1.10**	
	(0.931)		(0.309)		(0.028)	
L.logsovspread	-2.74***		-0.658		-1.81**	
	(0.000)		(0.204)		(0.024)	
D.logsovspread	-10.8		-16.2		-2.05	
	(0.242)		(0.150)		(0.534)	
banklevel_sovdiffs	2.54		3.59		0.641	
	(0.186)		(0.129)		(0.338)	
bankdiffs_sovdiffs	-3.34		-0.660		-0.308	
	(0.154)		(0.707)		(0.840)	
L.regcapratio	15.2		16.9		-6.48	
	(0.473)		(0.193)		(0.659)	
L.rwaratio	-23.6***		-10.1***		-12.2***	
	(0.000)		(0.006)		(0.000)	
sovlevel_regcap	0.052		-1.87		2.83	
	(0.990)		(0.464)		(0.365)	
sovlevel_rwaratio	4.21***		1.64**		2.25***	
	(0.000)		(0.029)		(0.002)	
L.depov_nba	-5.63**		-0.982		-3.72***	
	(0.035)		(0.702)		(0.004)	
LD.sovbonds	3.98		5.88		-0.142	
	(0.393)		(0.875)		(0.982)	
dealer		0.600***		0.598***		0.599***
		(0.000)		(0.0000)		(0.000)
absdif_sov		0.684		0.684		0.661
		(0.313)		(0.314)		(0.330)
lagdiff_ind		-1.06***		-1.07***		-1.06***
		(0.000)		(0.000)		(0.000)
posdtcc_ind		1.40***		1.40***		1.40***
		(0.000)		(0.000)		(0.000)
athrho	0.147***		0.087**		0.065**	
	(0.000)		(0.037)		(0.038)	
lnsigma	18.4***		-7.44***		-7.52***	
	(0.000)		(0.000)		(0.000)	
Constant	11.0***	-1.39***	5.04	-1.39***	8.81**	-1.39***
	(0.002)	(0.000)	(0.187)	(0.000)	(0.018)	(0.000)
Observations	20,316	20,316	20,316	20,316	20,316	20,316

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. "RWA ratio" 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.rwa_ratio", "sovlevel_RegCap", "sovlevel_RWARatio", "L.depov_nba" and the regression constant are presented in e+07 for column (1) and in e-04 for columns (3) and (5). The idependent variable "LD.sovbonds" 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-state pair level. ***, **, * denote statistical significances at 99%, 95% and 90% levels. P-values are in parenthesis.

Table 4. Heckman regressions (Robustness – Interval Split)

	January 2008 – November 2010						December 2010 – August 2013					
	(1) dif_dtcc	(2) select	(3) dif_dtcc_nba	(4) select	(5) dif_dtcc_debt	(6) select	(7) dif_dtcc	(8) select	(9) dif_dtcc_nba	(10) select	(11) dif_dtcc_debt	(12) select
LD.dtcc	0.173*** (0.003)						0.245*** (0.000)					
LD.dtcc_nba			0.259*** (0.000)						0.539*** (0.000)			
LD.dtcc_debt					0.053 (0.112)						-0.052 (0.587)	
L.logbankspread	1.13 (0.263)		0.895 (0.481)		0.294 (0.674)		-1.72*** (0.000)		-1.65*** (0.0042)		-0.880*** (0.001)	
D.logbankspread	-2.60*** (0.006)		-0.886 (0.277)		-1.97*** (0.008)		2.19 (0.593)		-1.99 (0.1810)		-0.271 (0.681)	
L.logsovspread	-3.90** (0.013)		-1.23* (0.086)		-2.43* (0.096)		0.954 (0.289)		-0.208 (0.8425)		0.547 (0.303)	
D.logsovspread	-24.9* (0.082)		-7.59 (0.613)		-11.4* (0.084)		-24.4*** (0.007)		-44.1* (0.0502)		0.996 (0.879)	
banklevel_sovdiffs	5.92* (0.053)		1.96 (0.536)		2.77** (0.049)		4.44*** (0.007)		8.69* (0.0536)		-0.136 (0.912)	
bankdiffs_sovdiffs	3.29 (0.292)		2.07 (0.330)		3.81* (0.086)		2.16 (0.661)		3.71 (0.1555)		-2.21 (0.127)	
L.regcapratio	28.4 (0.357)		12.9 (0.537)		-2.94 (0.889)		4.76 (0.889)		52.5 (0.2083)		22.1 (0.137)	
L.rwaratio	-31.8*** (0.000)		-13.4*** (0.000)		-16.1*** (0.007)		10.3 (0.170)		-11.0 (0.3503)		2.02 (0.504)	
sovlevel_regcap	-2.90 (0.642)		-1.38 (0.745)		1.32 (0.764)		-0.273 (0.964)		-6.73 (0.3970)		-2.00 (0.504)	
sovlevel_rwaratio	5.85*** (0.000)		2.26*** (0.004)		3.05** (0.030)		-0.742 (0.598)		2.05 (0.3190)		0.00984 (0.988)	
L.depov_nba	-11.0 (0.145)		-1.86 (0.559)		-4.94** (0.039)		-5.07 (0.320)		-4.26 (0.3149)		-3.70* (0.090)	
LD.sovbonds	9.68 (0.265)		-25.4 (0.511)		-8.14 (0.514)		0.124 (0.988)		12.2 (0.7433)		17.1 (0.169)	
dealer		0.533*** (0.000)		0.530*** (0.000)		0.535*** (0.000)		0.719*** (0.000)		0.718*** (0.000)		0.718*** (0.000)
absdif_sov		38.1*** (0.000)		38.1*** (0.000)		38.2*** (0.000)		0.684 (0.354)		0.679 (0.359)		0.681 (0.357)
lagdiff_ind		-1.03*** (0.000)		-1.04*** (0.000)		-1.03*** (0.000)		-1.07*** (0.000)		-1.07*** (0.000)		-1.07*** (0.000)
posdtcc_ind		1.35*** (0.000)		1.35*** (0.000)		1.35*** (0.000)		1.55*** (0.000)		1.55*** (0.000)		1.55*** (0.000)
Constant	13.9* (0.059)	-1.34*** (0.000)	2.26 (0.734)	-1.34*** (0.000)	0.108 (0.128)	-1.35*** (0.000)	-0.0279 (0.960)	-1.70*** (0.000)	8.06 (0.262)	-1.70*** (0.000)	-77.6 (0.800)	-1.70*** (0.000)
Observations	10,464	10,464	10,464	10,464	10,464	10,464	9,481	9,481	9,481	9,481	9,481	9,481

This table presents the estimates of the Heckman regressions split into two time subsamples. Columns (1-6) refer to the results with January 2008-November 2010, and (7-12) are the results with December 2010-August 2013 subsamples. Columns (2), (4), (6), (8), (10), and (12) contain the first-stage selection results, and columns (1), (3), (5), (7), (9) and (11) contain the second-stage main regressions. All variables are defined as in Table 3. The independent variables "L.logbankspread","D.logbankspread", "L.logsovspread", "D.logsovspread", "banklevel_sovdiffs", "bankdiffs_sovdiffs", "L.regcapratio", "L.rwa_ratio", "sovlevel_RegCap", "sovlevel_RWARatio", "L.depov_nba" and the regression constant are presented in e+07 for column (1), (7) and in e-04 for columns (3), (5), (9) and (11). The idependent variable "LD.sovbonds" is presented in e-03 for column (1), (7) and in e-15 for columns (3), (5), (9) and (11). The selection variable "absdif_sov" is presented in e-04 in columns (2), (4), (6), (8), (10) and (12). All errors are robust clustered at the bank-state pair level. ***, **, * denote statistical significances at 99%, 95% and 90% levels. P-values are in parenthesis.

Table 5. Heckman regressions (Robustness – without WestLB)

VARIABLES	(1) dif_dtcc	(2) select	(3) dif_dtcc_nba	(4) select	(5) dif_dtcc_debt	(6) select
LD.dtcc	0.186*** (0.000)					
LD.dtcc_nba			0.374*** (0.000)			
LD.dtcc_debt					0.0445 (0.195)	
L.logbankspread	0.512 (0.287)		-0.484 (0.492)		-0.016 (0.951)	
D.logbankspread	-0.0785 (0.954)		-0.901 (0.252)		-1.09* (0.055)	
L.logsovspread	-2.18*** (0.005)		-0.438 (0.354)		-1.59* (0.081)	
D.logsovspread	-12.8 (0.226)		-18.7 (0.136)		-2.11 (0.558)	
banklevel_sovdiffs	2.98 (0.178)		4.14 (0.118)		0.667 (0.365)	
bankdiffs_sovdiffs	-1.90 (0.445)		1.30 (0.455)		0.458 (0.782)	
L.regcapratio	39.1 (0.114)		31.1** (0.042)		5.84 (0.729)	
L.rwaratio	-24.1*** (0.000)		-10.8*** (0.003)		- 12.8*** (0.001)	
sovlevel_regcap	-3.99 (0.422)		-4.09 (0.183)		0.726 (0.840)	
sovlevel_rwaratio	4.15*** (0.000)		1.75** (0.016)		2.32*** (0.003)	
L.depov_nba	-6.60** (0.038)		-0.810 (0.7832)		-3.76*** (0.009)	
LD.sovbonds	5.23 (0.2696)		18.1 (0.6239)		2.33 (0.693)	
dealer		0.673*** (0.000)		0.672*** (0.000)		0.673*** (0.000)
absdif_sov		0.658 (0.397)		0.659 (0.396)		0.640 (0.410)
lagdiff_ind		-1.06*** (0.000)		-1.06*** (0.000)		-1.06*** (0.000)
posdtcc_ind		1.34*** (0.000)		1.34*** (0.000)		1.34*** (0.000)
Constant	8.06** (0.046)	-1.41*** (0.000)	4.49 (0.273)	-1.41*** (0.000)	7.78* (0.062)	-1.42*** (0.000)
Observations	19,020	19,020	19,020	19,020	19,020	19,020

This table presents the estimates of the Heckman regressions with the full sample without WestLB included. 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. All variables are defined as in Table 3. The independent variables "L.logbankspread","D.logbankspread", "L.logsovspread", "D.logsovspread", "banklevel_sovdiffs", "bankdiffs_sovdiffs", "L.regcapratio", "L.rwa_ratio", "sovlevel_RegCap", "sovlevel_RWARatio", "L.depov_nba" and the regression constant are presented in e+07 for column (1) and in e-04 for columns (3) and (5). The idependent variable "LD.sovbonds" 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-state pair level. ***, **, * denote statistical significances at 99%, 95% and 90% levels. P-values are in parenthesis.

Table 6. Heckman regressions (Dealers vs. non-Dealers)

VARIABLES	DEALERS						NON-DEALERS					
	(1) dif_dtcc	(2) select	(3) dif_dtcc_nba	(4) select	(5) dif_dtcc_debt	(6) select	(7) dif_dtcc	(8) select	(9) dif_dtcc_nba	(10) select	(11) dif_dtcc_debt	(12) select
LD.dtcc	0.0867 (0.282)						0.335*** (0.000)					
LD.dtcc_nba			0.198*** (0.005)						0.379*** (0.000)			
LD.dtcc_debt					-0.0187 (0.435)						0.231*** (0.000)	
L.logbankspread	0.122 (0.798)		0.0177 (0.865)		-0.117 (0.635)		1.36* (0.086)		-0.462 (0.717)		0.262 (0.538)	
D.logbankspread	0.553 (0.684)		0.196 (0.572)		-0.909 (0.163)		-0.00812 (0.997)		-1.80 (0.362)		-0.871 (0.319)	
L.logsovspread	-2.33** (0.011)		-0.908*** (0.000)		-2.36* (0.082)		-3.51** (0.018)		-0.390 (0.851)		-2.12** (0.017)	
D.logsovspread	-28.8 (0.104)		-2.41 (0.613)		-10.5* (0.063)		4.74 (0.605)		-27.5 (0.202)		3.95 (0.428)	
banklevel_sovdiffs	6.04 (0.104)		0.495 (0.610)		2.22* (0.055)		-0.487 (0.796)		6.20 (0.174)		-0.479 (0.632)	
bankdiffs_sovdiffs	-0.729 (0.776)		0.0192 (0.981)		0.195 (0.921)		-11.0** (0.039)		-5.81 (0.282)		-2.18 (0.436)	
L.regcapratio	-80.8*** (0.009)		-29.1*** (0.001)		-43.4* (0.076)		46.8 (0.230)		34.7 (0.314)		-10.0 (0.629)	
L.rwaratio	-3.07 (0.448)		-1.90 (0.214)		-7.36 (0.102)		-30.1*** (0.000)		-13.7 (0.128)		-13.1*** (0.001)	
sovlevel_regcap	17.5*** (0.010)		6.18*** (0.001)		9.74* (0.077)		-3.93 (0.597)		-5.59 (0.436)		4.42 (0.303)	
sovlevel_rwaratio	0.290 (0.729)		0.0282 (0.344)		1.59 (0.120)		5.43*** (0.000)		1.92 (0.322)		2.39*** (0.003)	
L.depov_nba	-4.77 (0.168)		-0.0253 (0.987)		0.761 (0.8472)		14.3* (0.085)		24.5** (0.0467)		-2.45 (0.512)	
LD.sovbonds	8.02 (0.108)		33.5 (0.399)		6.06 (0.187)		-35.7** (0.020)		-348.0** (0.011)		-89.8 (0.146)	
absdif_sov		0.858 (0.427)		0.845 (0.434)		0.838 (0.441)		0.545 (0.547)		0.558 (0.536)		0.520 (0.565)
lagdiff_ind		-1.29*** (0.000)		-1.29*** (0.000)		-1.29*** (0.000)		-0.927*** (0.000)		-0.928*** (0.000)		-0.925*** (0.000)
posdtcc_ind		1.28*** (0.000)		1.27*** (0.000)		1.28*** (0.000)		1.45*** (0.000)		1.45*** (0.000)		1.45*** (0.000)
Constant	10.6*** (0.003)	-0.569*** (0.000)	4.17*** (0.000)	-0.563*** (0.000)	10.6** (0.0488)	-0.571*** (0.000)	9.57 (0.199)	-1.53*** (0.000)	5.24 (0.6109)	-1.53*** (0.000)	9.26** (0.041)	-1.53*** (0.000)
Observations	3,844	3,844	3,844	3,844	3,844	3,844	16,472	16,472	16,472	16,472	16,472	16,472

This table presents the estimates of the Heckman regressions split into dealers and non-dealers samples. Columns (1-6) refer to the results with the dealers, and (7-12) are the results with non-dealers. Columns (2), (4), (6), (8), (10), and (12) contain the first-stage selection results, and columns (1), (3), (5), (7), (9) and (11) contain the second-stage main regressions. All variables are defined as in Table 3. The independent variables "L.logbankspread","D.logbankspread", "L.logsovspread", "D.logsovspread", "banklevel_sovdiffs", "bankdiffs_sovdiffs", "L.regcapratio", "L.rwa_ratio", "sovlevel_RegCap", "sovlevel_RWARatio", "L.depov_nba" and the regression constant are presented in e+07 for column (1), (7) and in e-04 for columns (3), (5), (9) and (11). The idependent variable "LD.sovbonds" is presented in e-03 for column (1), (7) and in e-15 for columns (3), (5), (9) and (11). The selection variable "absdif_sov" is presented in e-04 in columns (2), (4), (6), (8), (10) and (12). All errors are robust clustered at the bank-state pair level. ***, **, * denote statistical significances at 99%, 95% and 90% levels. P-values are in parenthesis.

Table 7. Heckman regressions (GIIPS vs. non-GIIPS)

	GIIPS						NON-GIIPS					
VARIABLES	(1) dif_dtcc	(2) select	(3) dif_dtcc_nba	(4) select	(5) dif_dtcc_debt	(6) select	(7) dif_dtcc	(8) select	(9) dif_dtcc_nba	(10) select	(11) dif_dtcc_debt	(12) select
LD.dtcc	0.232*** (0.000)						0.0999 (0.154)					
LD.dtcc_nba			0.285*** (0.000)						0.0443*** (0.000)			
LD.dtcc_debt					0.170* (0.055)						-0.00112 (0.952)	
L.logbankspread	0.582 (0.496)		0.376 (0.678)		-0.410 (0.362)		0.471 (0.354)		-0.534 (0.525)		0.220 (0.478)	
D.logbankspread	1.43 (0.577)		-0.0629 (0.945)		-1.44** (0.039)		-0.786 (0.453)		-1.13 (0.258)		-0.862 (0.216)	
L.logsovspread	-2.17** (0.040)		-1.46* (0.053)		-0.984 (0.121)		-3.35*** (0.0008)		-0.0895 (0.908)		-3.04* (0.057)	
D.logsovspread	-10.7 (0.513)		-2.62 (0.789)		-1.11 (0.831)		-6.22 (0.465)		-27.8 (0.147)		-2.15 (0.644)	
banklevel_sovdiffs	2.64 (0.442)		0.710 (0.720)		0.431 (0.670)		1.55 (0.382)		6.04 (0.136)		0.656 (0.497)	
bankdiffs_sovdiffs	-11.2*** (0.001)		-5.19 (0.105)		-2.98 (0.162)		-0.167 (0.951)		1.49 (0.470)		0.999 (0.628)	
L.regcapratio	86.7* (0.073)		66.1* (0.053)		32.7 (0.162)		-2.61 (0.919)		4.95 (0.764)		-33.4 (0.177)	
L.rwaratio	-30.7*** (0.001)		-22.7*** (0.000)		-15.7*** (0.005)		-23.0*** (0.000)		-3.32 (0.530)		-13.2** (0.015)	
sovlevel_regcap	-11.9 (0.159)		-10.5* (0.075)		-5.68 (0.185)		2.90 (0.573)		0.392 (0.911)		9.09 (0.112)	
sovlevel_rwaratio	5.39*** (0.001)		4.00*** (0.001)		2.84*** (0.005)		4.33*** (0.000)		0.340 (0.761)		2.65** (0.040)	
L.depov_nba	-7.12 (0.222)		-5.75* (0.071)		-4.53** (0.022)		-2.72 (0.395)		2.92 (0.421)		-2.64 (0.121)	
LD.sovbonds	0.675 (0.957)		31.3 (0.782)		5.19 (0.711)		5.48 (0.104)		0.0458 (0.997)		1.59 (0.752)	
dealer		0.721*** (0.000)		0.715*** (0.000)		0.716*** (0.000)		0.588*** (0.000)		0.589*** (0.000)		0.590*** (0.000)
absdif_sov		-0.361 (0.635)		-0.360 (0.638)		-0.380 (0.620)		16.7*** (0.007)		16.8*** (0.007)		16.6*** (0.008)
lagdiff_ind		-0.955*** (0.000)		-0.959*** (0.000)		-0.958*** (0.000)		-1.07*** (0.000)		-1.07*** (0.000)		-1.07*** (0.000)
posdtcc_ind		1.47*** (0.000)		1.47*** (0.000)		1.47*** (0.000)		1.34*** (0.000)		1.34*** (0.000)		1.34*** (0.000)
Constant	7.01 (0.308)	-1.37*** (0.000)	6.18 (0.2976)	-1.37*** (0.000)	7.75* (0.0631)	-1.37*** (0.000)	13.0*** (0.007)	-1.44*** (0.000)	2.76 (0.5418)	-1.45*** (0.000)	12.4* (0.0589)	-1.45*** (0.000)
Observations	4,885	4,885	4,885	4,885	4,885	4,885	15,431	15,431	15,431	15,431	15,431	15,431

This table presents the estimates of the Heckman regressions split into GIIPS and non-GIIPS samples. Columns (1-6) refer to the results with the GIIPS states, and (7-12) are the results with non-GIIPS states. Columns (2), (4), (6), (8), (10), and (12) contain the first-stage selection results, and columns (1), (3), (5), (7), (9) and (11) contain the second-stage main regressions. All variables are defined as in Table 3. The independent variables "L.logbankspread","D.logbankspread", "L.logsovspread", "D.logsovspread", "banklevel_sovdiffs", "bankdiffs_sovdiffs", "L.regcapratio", "L.rwa_ratio", "sovlevel_RegCap", "sovlevel_RWARatio", "L.depov_nba" and the regression constant are presented in e+07 for column (1), (7) and in e-04 for columns (3), (5), (9) and (11). The idependent variable "LD.sovbonds" is presented in e-03 for column (1), (7) and in e-15 for columns (3), (5), (9) and (11). The selection variable "absdif_sov" is presented in e-04 in columns (2), (4), (6), (8), (10) and (12). All errors are robust clustered at the bank-state pair level. ***, **, * denote statistical significances at 99%, 95% and 90% levels. P-values are in parenthesis.

Table 8. Heckman regressions (GIIPS Dealers vs. GIIPS non-Dealers)

VARIABLES	GIIPS & DEALERS						GIIPS & NON-DEALERS					
	(1) dif_dtcc	(2) select	(3) dif_dtcc_nba	(4) select	(5) dif_dtcc_debt	(6) select	(7) dif_dtcc	(8) select	(9) dif_dtcc_nba	(10) select	(11) dif_dtcc_debt	(12) select
LD.dtcc	0.158** (0.016)						0.362*** (0.000)					
LD.dtcc_nba			0.273*** (0.000)						0.267*** (0.002)			
LD.dtcc_debt					-0.0434 (0.274)						0.317*** (0.000)	
L.logbankspread	-0.0351 (0.977)		-0.0824 (0.753)		-0.533 (0.147)		1.68 (0.230)		1.18 (0.476)		-0.079 (0.915)	
D.logbankspread	3.28 (0.357)		0.397 (0.542)		-0.887 (0.323)		-1.05 (0.618)		-0.120 (0.955)		-1.12 (0.288)	
L.logsovspread	2.39*** (0.001)		-0.395 (0.229)		0.368 (0.658)		-8.00*** (0.001)		-6.24*** (0.006)		-4.03* (0.051)	
D.logsovspread	-31.5 (0.438)		2.41 (0.804)		-4.53 (0.634)		-1.65 (0.883)		-8.45 (0.576)		-3.00 (0.714)	
banklevel_sovdiffs	6.86 (0.425)		-0.370 (0.851)		0.952 (0.614)		0.709 (0.748)		1.95 (0.522)		0.872 (0.591)	
bankdiffs_sovdiffs	-6.58 (0.196)		-1.77 (0.186)		-3.07 (0.194)		-15.7** (0.024)		-13.8* (0.067)		-2.97 (0.478)	
L.regcapratio	84.9*** (0.004)		-0.591 (0.951)		18.9 (0.431)		76.5 (0.547)		73.8 (0.439)		10.1 (0.830)	
L.rwaratio	-6.10 (0.426)		-4.33** (0.041)		-5.23 (0.236)		-61.6*** (0.000)		-48.0*** (0.000)		-29.8** (0.014)	
sovlevel_regcap	-12.5** (0.037)		1.17 (0.555)		-3.52 (0.438)		-7.24 (0.719)		-7.79 (0.619)		-0.203 (0.981)	
sovlevel_rwaratio	-0.149 (0.916)		0.652* (0.053)		0.731 (0.396)		11.0*** (0.000)		8.96*** (0.000)		5.54** (0.013)	
L.depov_nba	-20.6*** (0.003)		-1.47 (0.735)		-6.36* (0.053)		14.7 (0.375)		-4.18 (0.807)		-5.25 (0.477)	
LD.sovbonds	8.07 (0.585)		72.5 (0.552)		14.2 (0.271)		-21.2 (0.222)		-211.0 (0.160)		-22.3 (0.724)	
absdif_sov		-0.329 (0.747)		-0.372 (0.724)		-0.350 (0.742)		-0.373 (0.717)		-0.347 (0.736)		-0.392 (0.706)
lagdiff_ind		-0.957*** (0.000)		-0.964*** (0.000)		-0.958*** (0.000)		-0.954*** (0.000)		-0.955*** (0.000)		-0.952*** (0.000)
posdtcc_ind		0.812*** (0.000)		0.809*** (0.000)		0.827*** (0.000)		1.54*** (0.000)		1.54*** (0.000)		1.55*** (0.000)
Constant	-9.97 (0.241)	-6.06 (0.975)	2.01 (0.2123)	-1.00 (0.996)	1.87 (0.6564)	-21.3 (0.916)	33.9** (0.015)	-1.43*** (0.000)	25.2* (0.066)	-1.43*** (0.000)	22.1* (0.050)	-1.44*** (0.000)
Observations	925	925	925	925	925	925	3,960	3,960	3,960	3,960	3,960	3,960

This table presents the estimates of the Heckman regressions with GIIPS states only, split into dealer and non-dealer samples. Columns (1-6) refer to the results with the dealer activity on GIIPS states, and (7-12) are the results with the non-dealer activity on GIIPS states. Columns (2), (4), (6), (8), (10), and (12) contain the first-stage selection results, and columns (1), (3), (5), (7), (9) and (11) contain the second-stage main regressions. All variables are defined as in Table 3. The independent variables "L.logbankspread","D.logbankspread", "L.logsovspread", "D.logsovspread", "banklevel_sovdiffs", "bankdiffs_sovdiffs", "L.regcapratio", "L.rwa_ratio", "sovlevel_RegCap", "sovlevel_RWARatio", "L.depov_nba" and the regression constant are presented in e+07 for column (1), (7) and in e-04 for columns (3), (5), (9) and (11). The idependent variable "LD.sovbonds" is presented in e-03 for column (1), (7) and in e-15 for columns (3), (5), (9) and (11). The selection variable "absdif_sov" is presented in e-04 in columns (2), (4), (6), (8), (10) and (12). The selection constant is presented in e-03 in columns (2), (4), and (6). All errors are robust clustered at the bank-state pair level. ***, **, * denote statistical significances at 99%, 95% and 90% levels. P-values are in parenthesis.