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TESI DI LAUREA

"THE BANKS' USAGE OF CDS: HEDGING OR CAPITAL RELIEF? AN EMPIRICAL ANALYSIS OF ITALIAN BANKS"

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Abstract

This dissertation analyzes the banks' usage of Credit Default Swap. Although it is almost a new entry in the financial market, since its creation in the early 1990's, it has been a well–known instrument, particularly in the subprime mortgages crisis the world talked a lot of that.

Therefore, given its popularity, this topic has been worldwide broadly studied in the financial literature but with this work we want to contribute focusing in the domestic context. We develop our own dataset with eight Italian's major banks for a period ranging from 2004 to 2018, with a concentration in testing two main hypothesis: capital relief or hedging instrument.

The empirical analysis is based on a panel dataset and we perform a Fixed Effect and Random Effect regression models.

Results show evidence of banks using Credit Default Swap protection as capital relief instrument in all the specifications but results on the hedging hypothesis are ambiguous within the different statements and we deeply motivate this outcome.

KEY WORDS: Credit Default Swap, Banks, Hedging instrument, Capital relief.

Contents

Introduction

Credit Default Swap (CDS) is one of the main protagonist of the financial markets in the recent turmoil and this has emphasized the necessity to better understand how it works and which are its implication for the policymaker, banks and other financial operators.

We report as its date of born the years 1994 when J. P. Morgan first launched the Credit Default Swap. Originally, was created in order to have an instrument able to hedge the riskier exposures, i.e. an individual that lend money to third party, is exposed to the credit risk that this counterparty at the time of repayment is no longer able to fulfil his obligation. If such threat exists one may want to be protected from this possibility and the Credit Default Swap aims to do that.

In particular, the CDS allows individual to buy a protection from whatever protection seller that is willing to sell that prevention from a counterparty's risk of default. Where the counterparty is the entity with which the individual has made the contracts, lending or, generally, the agreements.

On the other hand, in the most recent years, the types of use made of the Credit Default Swap protection have increased exponentially. In describing some of them, we mainly follow Aldasoro and Barth (2017) and Minton *et al.* (2008) who tested several hypothesis other than the hedging and capital relief ones, such as the private information example, which asserts that banks in some lending exposures may have sensible private information on the borrowers and create information asymmetries that affect the actual and original use of CDS, turning it into a speculative instrument.

Therefore, in this dissertation we focus only on two of them and we construct our own dataset that contains 8 Italian banks, considered in the time–window of fourteen years, from 2004 to 2018. We construct a measure of the share of the loan that banks lend to their customer (either individual, firms or other banks) that remains uninsured, in particular, we calculate the portion of the bank' exposure that is not protected by a CDS contract.

In that way we apply the model to our sample and perform a panel data regression model with a Within Group, Between Effect and Random Effect regressions of the data.

We contribute to the existing literature by analysing data before and during the financial crisis for the Italian major banks.

The remainder of the paper is organized as follows. In Chapter 1, we present an overview of the Credit Default Swap instrument deepening in its use, regulation, function and popularity from its first implementation. In Chapter 2, we present specifically the relationship between banks and our interesting instrument, reviewing the past literature' hypothesis and the results obtained in order to have an idea of the variety of uses that has been made of the Credit Default Swap. In this Chapter we also emphasize the role of the Rating Agencies in determining the credit risk of the counterparty, an essential and extremely useful valuation if a bank want to have an external estimate of the counterparty's probability of default.

Finally, in Chapter 3 we describe the data we use and present the empirical set–up of our analysis together with the corresponding comments on the results we find out.

Chapter 1

1 Credit Default Swap

In this Chapter, a brief introduction and overview of the Credit Default Swap contract are going to be provided; underlying its functioning, historical trend, but even some problems related to its implementation.

1.1 Credit Default Swap definition

In 1994, J.P. Morgan, a leader in financial services, first launched a Credit Default Swap contract (CDS) with the aim to protect its credit risk exposure to Exxon. At that time J.P. Morgan handles the exposure by paying a fee to the European Bank for Reconstruction and Development, which was willing to sell protection. This is exactly the way in which a CDS works: it acts as an insurance contract offering protection against the default of a referenced sovereign government, corporation, or structured entity (Augustin *et al.*, 2014).

Technically speaking, a CDS is a contract accessory to a loan or other instruments and techniques, particularly is a fixed income derivative instrument, that permits a protection buyer to purchase insurance against a credit event, that may happen, on an underlying reference entity, by paying an annuity premium to the protection seller.

We refer to this annuity premium as the CDS spread, over the life of the contract, usually defined as a percentage of the notional amount insured (or in basis points) that can be paid in quarterly or semi–annual instalments. For example, if there are some suspect on a company' creditworthiness (i.e. on your reference entity) you would be incentivised to buy a CDS protection on that company. Then, if some default event occurs, like the company fail to meet its obligations for any of a predetermined set of its debt claims, it would trigger the payout from the entity that has sold you the CDS contract (i.e. the protection seller). Clearly, the higher is the insolvency risk perceived by the market, the higher will be the premium charged on the instrument.

The majority of credit event considered able to trigger the payment are reference entity bankruptcy, failure to pay, obligation acceleration, repudiation and moratorium.

Actually, the Credit Default Swap often incorporates a specific class of the firm's capital structure, such as the senior, unsecured, or junior debt obligations of the company and references a particular amount of the insured debt, is defined as the notional amount.

The transaction's terms and conditions, including its maturity date and which credit events are covered by the contract, are defined in the trade "Confirmation". Standard Confirmations reference the 2003 ISDA – International Swaps and Derivatives Association – credit derivatives definitions (the "Definitions") and supplements are contained in the May 2003 Supplement and the 2009 ISDA Credit Derivatives Determinations Committees, Auction Settlement and Restructuring Supplement. These provide the basic framework for Credit Default Swap contracts and provide the standard set of definitions and provisions that govern the majority of CDS transactions. The aim of this document is to outline and discuss the most salient points (Credit Suisse, 2011). All this, just mentioned, documentation will be further analyzed in the following Sections.

Generally, Credit Default Swap not only aims to provide protection from exposure to risks but rather, it expresses, a positive or negative credit view (i.e. valuation of the creditworthiness) on a single entity or a portfolio of entities, independent of any other exposures to the entity one might have. Indeed, exist also the so called "naked CDS", a derivative contract for which having an actual credit risk exposure toward a reference entity is not a necessary condition; thus, for instance, a third party that wants to buy a CDS protection on the default of a company, can do it without having any type of credit risk exposure with this company.

Moreover, a CDS is a bilateral contract traded Over the Counter (not regulated markets). Trades in CDS markets face therefore, some impediments besides the default risk such as information asymmetries, transaction costs, searching costs, funding costs, etc. (Kamga *et al.*, 2017).

This characteristics of the CDS contracts, indeed, have created a lot of problems and we go through them in Section 1.3 and also in Section 1.2.4 where the regulation behind these issues, mainly in term of transparency and information, are taken into consideration.

1.2 History of instrument

1.2.1 Origins of Credit Default Swap

As already said the first–time adoption of a Credit Default Swap contract date back to 1994 when J.P. Morgan[1] created a CDS. Of course, is a very recent discovery but, despite is almost a novelty for financial markets, many strategic uses of the instrument have been made in several different manners.

However, Figure 1.1 presents a timeline for the Credit Default Swap market from its born date until 2014, twenty years of changes for this new market.

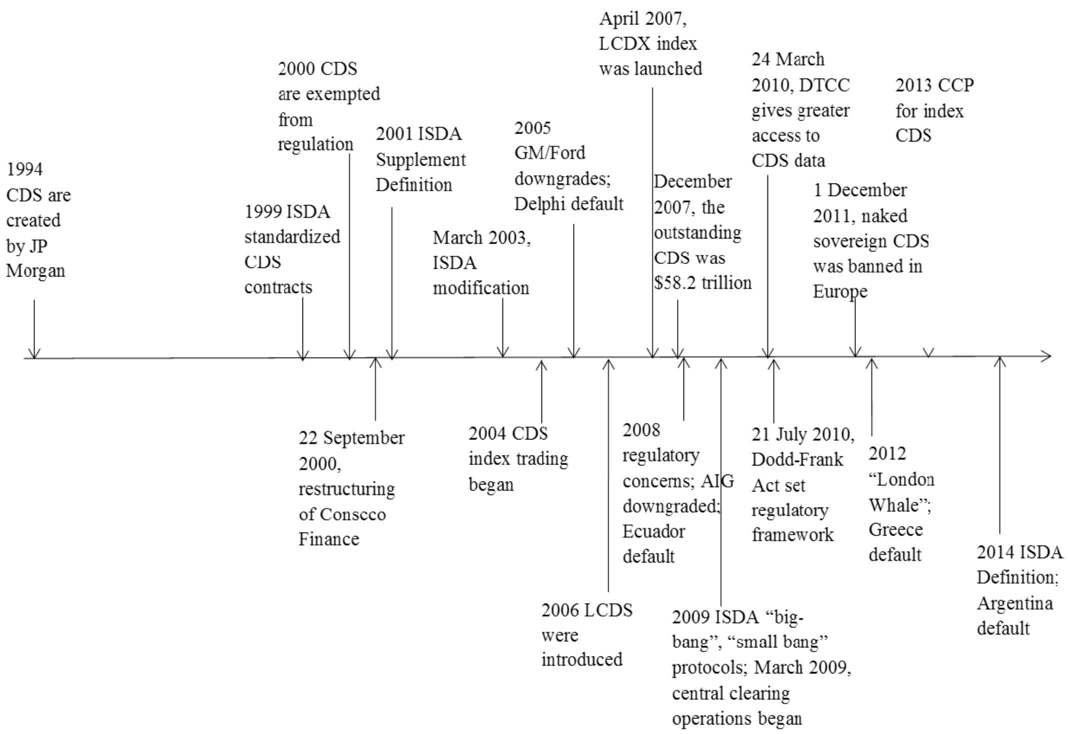

Figure 1.1: Timeline of the major developments in the CDS market from 1994 to 2014[2].

[1] J.P. Morgan Chase and Co. is an American multinational investment bank and financial services company headquartered in New York City.

[2] Source: Augustin P., Subrahmanyam M. G., Tang D. Y. and Wang, S. Q. (2014). Credit default swaps: A survey, Foundations and Trends in Finance.

As the figure suggests, only after five years from the first implementation there was the ISDA standardization of the instrument which was then revised later on in 2001. ISDA framework has become the most relevant standard for documenting Credit Default Swap transactions both at the national and international levels. ISDA – The International Swaps and Derivatives Association is an association created and managed in order to guarantee supervision and regulation over the derivative contracts subscribed in Over the Counter markets. The contracts established by ISDA are defined as "ISDA Master Agreement".

That Master Agreement refers to a contract between two counterparties that often pre–exists the CDS transaction in which they are about to enter. The master agreement governs the legal aspects in the relationship between parties that are not specific to the CDS transaction at hand, highlighting also the procedures related to the default event (Bomfim, 2005).

In the early 2000s, the market was growing sensationally until 2007, then something happened in 2008, the Lehman bankruptcy and the conditions changed dramatically. In the following paragraph, a more detailed and complete picture of the historical trend of the Credit Default Swap contract is provided.

More importantly, originally CDS were created for hedging purpose, indeed the primary objective of J.P. Morgan was to transfer the credit risk exposure that it had toward Exxon. But then, as time passed, the reasons why the instrument has been used, changed a lot and took various forms and banks, in particular, were the dominant players in the market, as CDS were primarily used to hedge risk in connection with its lending activities. This is one of the main reasons why our focus will be on the relationship between banks and the credit derivative instrument, which will be analyzed better in the Second Chapter. We further concentrate our attention on Single–name CDS, which definition is given in the next Section, since, as pointed out by Augustin *et al*. in 2014, most of the studies on Credit Default Swap market focus on the Single–name segment, this guarantee comparability with available studies.

1.2.2 Characteristics of CDS

The CDS market, generally speaking, could be segmented into two components:

- *Single–name CDS*: which are credit derivatives, where the reference entity is a specific debtor such as a non–financial corporation, a bank/dealer, or a sovereign (e.g. government bonds);

- *Multi–name CDS*: which incorporates index CDS, tranced index CDS and others, refer instead, on contracts where the reference entity is composed of more than one.

The main difference between the two regards the protection premium. Entering a portfolio of Single–name CDS means bear each single fair–market premium, instead in the Multi–name all the contracts share the same premium where the premium is established at base date and is set to have a net present value near zero; then, as the spread moves, the NPV became higher or lower than zero. Figure 1.2 plots the time series notional amount of both Single and Multi–name Credit Default Swap.

The most common CDS indices are those managed by the Markit group, which include indexes on European issuers with the most liquid Single–name CDS (iTraxx indices) and those covering US issuers (CDX indices). The growing diffusion of CDS indices depends on the fact that they offer a simple and immediate tool, especially for institutional investors, to cover the credit exposure on a portfolio of securities with a single transaction.

Credit Default Swap can even be referenced against customized exposure levels based on specific client demands: for example, can provide protection against the first $1 millions of realized credit losses in a $10 million portfolio of exposure. Such structures are commonly known as tranche of CDS.

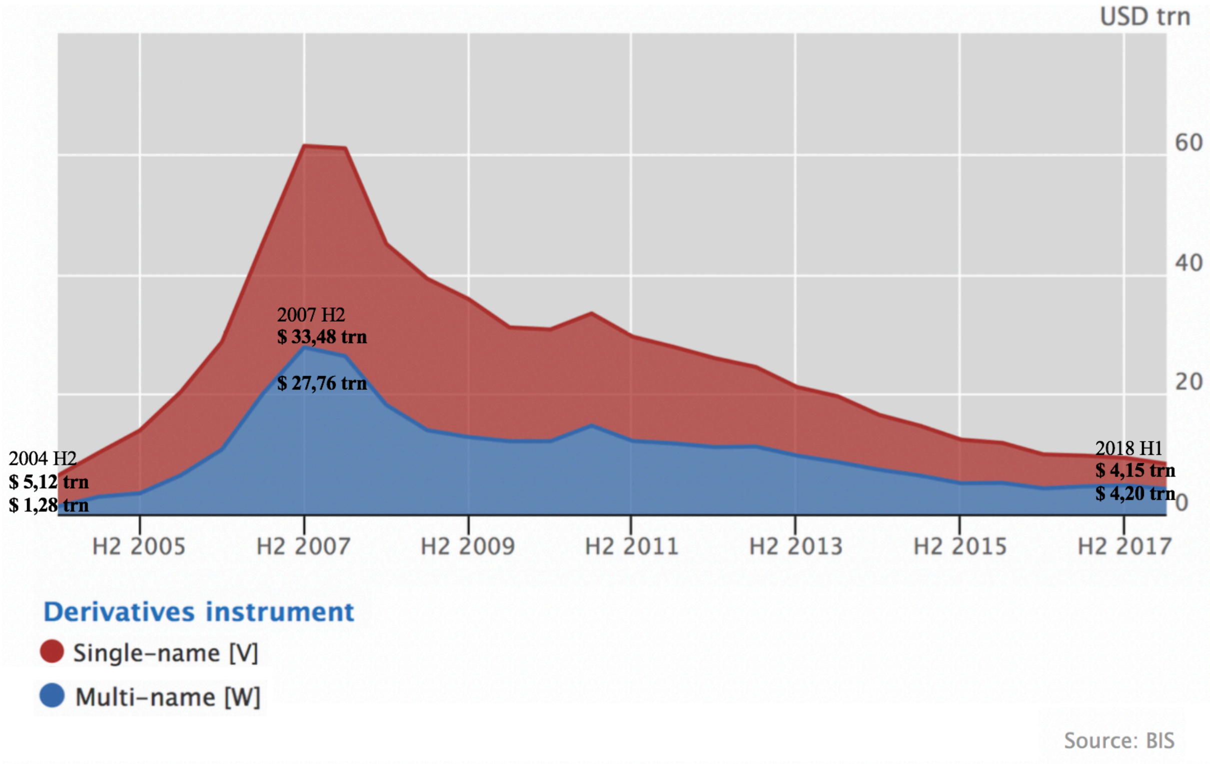

Figure 1.2: Notional amounts of Single–name and Multi–name CDS outstanding.

Deeply in Table 1.1 is presented the time series of the notional amounts outstanding of the total credit derivative in circulation (where H1 and H2 stand for first and second semester of the year) with the relative portion of CDSs in order to demonstrate their undeniable relevance, indeed from 2007 onward, CDS instruments represent almost 80/90% of the total credit derivatives.

We retrieved these data from the source of Bank for International Settlements (BIS)[3] that provides information about Credit Default Swap from the second semester of 2004 and we rearranged them in a way that emphasize specific elements. Indeed, another evidence that this table highlights is the fact that, overall, the Single–name Credit Default Swap represents the great component of the total notional amounts of Credit Default Swap in circulation, roughly always above the 50% of the total CDS.

[3] Bank for International Settlements (BIS) was established in 1930 and it's an international financial institution owned by 60 central banks which has the aim to serve central banks in their persuit of monetary and financial stability, to foster international cooperation and act as bank for central banks.

Global OTC derivatives market
In billions of US dollars

	Notional amounts outstanding													
	H1 2012	H2 2012	H1 2013	H2 2013	H1 2014	H2 2014	H1 2015	H2 2015	H1 2016	H2 2016	H1 2017	H2 2017	H1 2018	H2 2018
Credit derivatives	**28.202**	**26.329**	**24.845**	**21.526**	**19.954**	**16.846**	**14.987**	**12.644**	**11.994**	**10.103**	**9.967**	**9.578**	**8.582**	**8.373**
Credit default swaps (as a percentage of the credit derivatives)	**99% 27.806**	**99% 25.937**	**98% 24.469**	**98% 21.142**	**98% 19.581**	**98% 16.507**	**98% 14.689**	**98% 12.379**	**99% 11.847**	**98% 9.931**	**98% 9.727**	**98% 9.354**	**97% 8.346**	**97% 8.143**
Single–name instruments (as a percentage of tot CDS)	58% 16.036	57% 14.774	54% 13.211	54% 11.401	56% 10.920	55% 9.109	56% 8.265	58% 7.237	56% 6.639	54% 5.365	52% 5.101	49% 4.570	50% 4.148	49% 3.954
Multi–name instruments (as a percentage of tot CDS)	42% 11.770	43% 11.162	46% 11.258	46% 9.741	44% 8.661	45% 7.398	44% 6.424	42% 5.142	44% 5.208	43% 4.295	48% 4.626	51% 4.784	50% 4.199	51% 4.189

Global OTC derivatives market
In billions of US dollars

	Notional amounts outstanding														
	H2 2004	H1 2005	H2 2005	H1 2006	H2 2006	H1 2007	H2 2007	H1 2008	H2 2008	H1 2009	H2 2009	H1 2010	H2 2010	H1 2011	H2 2011
Credit derivatives	**11.653**	**15.958**	**19.992**	**27.925**	**37.150**	**51.095**	**68.066**	**68.677**	**51.910**	**46.065**	**42.816**	**31.416**	**31.089**	**33.811**	**29.911**
Credit default swaps (as a percentage of the credit derivatives)	**55% 6.396**	**64% 10.211**	**70% 13.908**	**73% 20.352**	**77% 28.650**	**88% 45.179**	**90% 61.242**	**89% 60.844**	**87% 44.943**	**85% 39.140**	**84% 35.783**	**99% 31.057**	**99% 30.718**	**99% 33.375**	**99% 29.511**
Single–name instruments (as a percentage of tot CDS)	80% 5.117	72% 7.310	75% 10.432	68% 13.873	62% 17.879	56% 25.104	55% 33.484	57% 34.557	60% 26.758	64% 25.177	64% 22.945	61% 18.920	61% 18.585	56% 18.639	59% 17.340
Multi–name instruments (as a percentage of tot CDS)	20% 1.279	28% 2.901	25% 3.476	32% 6.479	38% 10.771	44% 20.075	45% 27.758	43% 26.287	40% 18.185	36% 13.963	36% 12.837	39% 12.136	39% 12.134	44% 14.736	41% 12.171

Table 1.1 Notional amounts of total credit derivative and CDS outstanding.

Credit events

One of the most important characteristics of CDS as mentioned above is the *definition of the credit* event that triggers the payout. A detailed classification is provided by the Credit Derivatives Definitions in 1999, supplemented in 2001. However, is not sufficient recognize which are these credit event, but they must satisfy a minimum requirement in order to be qualified as a trigger event. For instance, the event should not be occasionally but has to persist for some time; more, it has to be notified and verified by a source of information like Bloomberg or Thomson Reuters.

A brief description of each event, that recall the one provided by the Credit Derivative Definitions, is given by Bomfim in 2005 and is the following:

- *Failure to pay*;
- *Bankruptcy*: is a condition where the reference entity becomes unable to repay the debt. This credit event doesn't apply to CDS written on sovereign entity;
- *Restructuring*: occurs when the term of the obligation change. Actually, Restructuring conventions differ between corporate and sovereign CDS contracts, from American and European companies and, even, among sub and senior European insurance Credit Default Swap contracts. It is therefore important to know what conventions are applicable and the implications (details in Section 1.2.3);
- *Obligation acceleration*: is a situation in which the payment is required earlier with respect to the previously established date;
- *Repudiation or moratorium*: is deemed to have occurred when the reference entity rejects or challenges the validity of its obligations.

Settlement following credit events

Furthermore, when a credit event occurs (i.e. the event that causes the payout of the seller), the buyer of protection stops to pay the spread (which represents the periodically payments due from the buyer to the seller for the entire contract life) in the last coupon payment date before the credit event and the seller of the protection has to deliver the notional amount of the Credit Default Swap contract.

That *settlement of Credit Default Swap* may be either physical or in cash. The choice of settlement method is specified in the Confirmation letter, which is part of the CDS documentation that specifies the identity of the reference entity, the notional amount (also known as “fixed rate payer calculation amount”) of the contract and the protection premium, more, it also determines the types of debt securities that can be delivered in the case of physically settled contracts.

Indeed, physical delivery requires the payment of the notional price against the delivery of the referenced activity (bond or loan). On the contrary, in case of cash settlement of the Credit Default Swap contract, the amount paid is the difference among notional price and its market price at the date of the settlement. More, cash–settled Credit Default Swap contracts are more common in the European Union rather than in the United States, where physical settlement is the method of choice.

Overall, initially, credit events were resolved via physical settlement, thus by delivering a bond to the protection’s seller for par value. That worked well as long as the holder of the CDS held the underlying bond and the instrument was mainly used as hedging derivative, but things, at some point, changed and from a hedging tool the CDS moved to be a betting instrument, thus then the physic delivery became difficult to implement.

However, an important consideration is that, in the credit event situation, the buyer of protection (short risk) delivers bonds and/or loans (in case of physical delivery and its face amount equal to the notional amount of the CDS) of the defaulted reference entity and receives par from the seller (long risk).

Therefore, additional risk to the protection buyer is that the protection seller may not be able to pay the full par amount upon default. This risk, referred to us as counterparty credit risk and, following Beinstein and Scott (2006), it is determined as the par value less the recovery rate, where the recovery rate here is the difference between the face value of the Credit Default Swap contract and the price at which bonds or loans delivered are traded when CDS contracts are settled.

Maturities

Another distinction is made by the *maturities*. Although the negotiation takes place Over the Counter, therefore creating a range for personalization of the contract, the maturities of a Credit

Default Swap are quite standard. Hence CDSs may have a maturity of one, five, seven or ten years.

The most commonly used, thus the relevant component of CDS in circulation, are those with a scheduled termination date of five years. They represent the most liquid tenors among all outstanding credit derivatives. Moreover, the coupon payments could occur every trimester, semester or on yearly basis, despite the one with the payment every 3 months is the widely used, which by convention take place on the following date: 20 March, 20 June, 20 September and 20 December.

1.2.3 Historical trend

In the years following its inception, the Credit Default Swap market saw a steady increase in volumes followed by a rapid surge in growth up to the Great Financial Crisis of 2007–2009. The size of the market and the role it played in the crisis led to calls for strengthened transparency and resilience (Aldasoro *et al.*, 2018).

On the contrary, the reverse trend characterizing the period after the subprime crisis, there was a particularly felt decrease in confidentiality about financial markets which in turn triggered the less willing to take risks by operators. Especially, after the mandatory disclosure required by the new regulation of that time, which figure out what the bubble was hidden.

Before going directly to the consequences, let's recall all the salient moments, indeed by the end of 2004 the total gross notional amount of CDS outstanding was roughly 6 $ trillion, as can be seen from Figure 1.3, instead, just prior the financial crisis the amount reached was almost 60 $ trillion, thus 10 times the prior evaluation. That was a period of strong development for the instrument, people and organizations started using it not only such a hedging tool, as was the idea behind its creation, but also for speculation purposes, for exploiting insider information gained from lending relationship[4] or, even, for a more aggressive behaviour in terms of risk–taking (Aldasoro *et al.*, 2017).

The following data and figures are all retrieved from Bank for International Settlements (BIS) and present the patterns for all CDS' instrument types (i.e. both Single–name and Multi–name CDS).

[4]Acharya and Johnson (2007) found out that with private information on loan quality, banks have an incentive to give more bad loans, provided they can then perform credit risk transfer via, for instance, CDS.

Figure 1.3 shows the total gross notional amount of Credit Default Swaps outstanding over the last 14 years from 2004 to 2018 (the amounts are in Trillion).

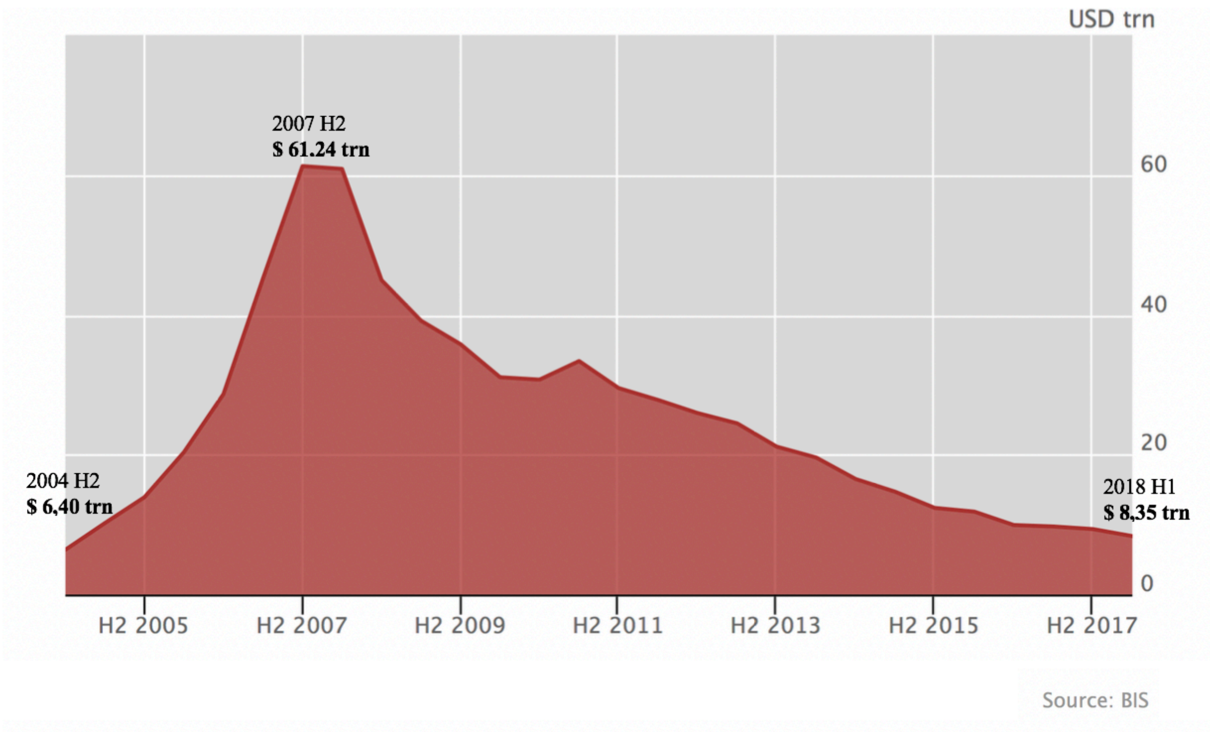

Figure1.3: Notional amounts of Credit Default Swap outstanding.

In the second half of 2007, as already mentioned, the notional amounts of CDS was 61.24 $ trillion, while in the first semester of 2018 reached almost the pre–crisis level. In terms of notional amounts outstanding, the market has seen a continuous decline after that peak in 2007 indeed declined up to 8.35 $ trillion.

The major events that marked the Credit Default Swap trend depicted in Figure 1.3 are now described. Market shocks like the Conseco Finance restructuring in 2000, the 2008 AIG bailout and the 2012 Greek default all contributed to shaping the formalization of Credit Default Swap contracts.

The Conseco Finance restructuring is a consequence of one of the main documentation issue in the history of the credit derivatives market, i.e. the definition of restructuring as a credit event. Specifically, the restructuring, among the credit events, is the one that has created more problems and was pointed out by Conseco.

In September 2000, Conseco (an American insurance company) lengthen the deadline on some loan and consequently modified the coupons.

That initiative caused the trigger of the credit event which, de facto, did not translate into unfavourable consequences for holders of debt. Rather, the protection buyer gained both from the payout of the CDS and, more, from the debt restructuring.

That episode caused the ISDA to take care of the argument that indeed defined some type of contract. Hence, the Credit Default Swap contract could trade with four different Restructuring conventions; first, the so–called "No R" which do not recognised the restructuring as a credit event; second, the "Old R" that do recognise the restructuring as possible trigger event and the settlement is as the one of the other credit events, thus without any limitation of the type of bond to deliver; third, "Mod–R" introduced in 2001, is a version of the Restructuring credit event where the instruments eligible for delivery is restricted (i.e. only those with a maturity equal or less than 30 months from the restructuring date); finally, the "Mod–Mod–R" (i.e. the Modified Modified Restructuring) that was established in 2003 and is similar to the Mod–R except for allowing a slightly larger range of deliverable obligations in the case of a restructuring event, thus extended to bond with a maturity up to 60 months after the restructuring.

More, as preannounced, the great recession in 2007–2009 contributed to the reduction in the notional amount, indeed it has led to a simultaneous decrease of both Single–name and Multi–name CDS. In the aftermath of this well–known event is evident that started a sentiment of fear with a consequent compression of credit derivative contracts, especially CDS which are the plain vanilla of that type of derivative instruments.

Actually, there still exists a discussion about why during the great financial crisis Lehman Brothers wasn't helped, while other institutions like Bear Sterns or AIG were saved.

In particular, the American International Group (AIG) was an American society which by the end of 2007 was heavily exposed in CDS market and used a great part of the premium received in order to reinvest money in Mortgage–Backed Securities (MBS), bond deriving from the securization of mortgages.

Initially, return as a profitable procedure but then, once there was the burst of the Subprime mortgages bubble and the default of Lehman Brothers, dealers who previously asked to the insurance company AIG protection, at that point in time started to ask for even more protection but the company was no longer able to provide it. Thus, the crush and the subsequent decision to save AIG demonstrates the relevance of the complexity and opacity behind the Credit Default Swap market: Lehman was a major CDS buyer, on which a substantial amount of protection had been sold, among others by AIG. At that time, consequential policy decisions were taken, despite authorities' limited knowledge regarding the structure of counterparty credit exposures and CDS protection sold.

Just after the “subprime crisis phase”, the CBOE VIX[5] peaks, the Credit Default Swap default premium also peaks. Thus, in this period of fragile financial markets, with weak funding conditions, high risk aversion and high credit risk, investors were less confident, less optimistic and shy away from risky assets.

Around 2010, the credit quality of several European countries crumbles, leading to their downgrade. This casts doubt on the capacity of governments to stabilize the–financial market, investors became less inclined to sell insurance against increasing default risk and supply less protection (Kamga *et al.*, 2017).

More, another scandalous event that marked the CDS history was the 2012 J. P. Morgan “London Whale” CDS trading loss. London Whale was the nickname of a well–known trader, the Chief Investment Officer of J.P. Morgan, Bruno Iksil. He had his popularity to the large positions on Credit Default Swap investment, the same condition that makes him fail in his objective that, as CIO of the bank, was to hold down the bank’s risk level. Iksil used 350 $ billion to invest (much of it derived from federally insured deposits) and become a money maker, with its London’s office focused on complex derivative trades that had less and less to do with hedging (as reported by Bloomberg LP in 2013); the estimated loss from the operation was about 6.2 $ billion.

An international episode, that has made the world talk about Credit Default Swap market again in recent years, was the Greece default. That circumstance remarked the fact that there is huge speculation behind its market and more importantly, shed light on what was considered up to that moment an innocuous instrument, the CDS, to be a very dangerous one.

American banks were sellers of protection and should guarantee the payout in case of Greece’ default, hence, the creditors of the state’s debt felt safe, but this was a huge error. Since when the moment in which the protection sellers had to pay, i.e. when the default event occurred, they did not. The circumstance considered by Fitch as the trigger credit event was the cut of 50% of the nominal value of Greece’ sovereign bond.

The ISDA established that there should not be the repayment of the Credit Default Swap which, in this situation became a useless insurance instrument, since it fails in its objective and creditors lost a lot of money. The motivation by ISDA was that the event wasn’t an actual credit event since there was a voluntary intention of restructuring the debt of Greece with a consistent haircut of the debt. A paradoxical situation that could effectively undermine the credibility of

[5] The CBOE VIX is a Volatility Index (i.e. VIX) created by the Chicago Board Options Exchange (CBOE). It is a real–time market index that represents the market's expectation of 30–day forward–looking volatility. Derived from the price inputs of the Standard and Poor 500 index options, it provides a measure of market risk and investors' sentiments.

the derivative market and contribute to the incessant decline in Credit Default Swap gross notional amount.

At this point, a remarkable and detailed study of the regulation behind CDS should be made, but before deeply investigate all the concerns of this wide theme is important to focus on a characterizing feature: the main counterparties sectors (shown in Figure 1.4).

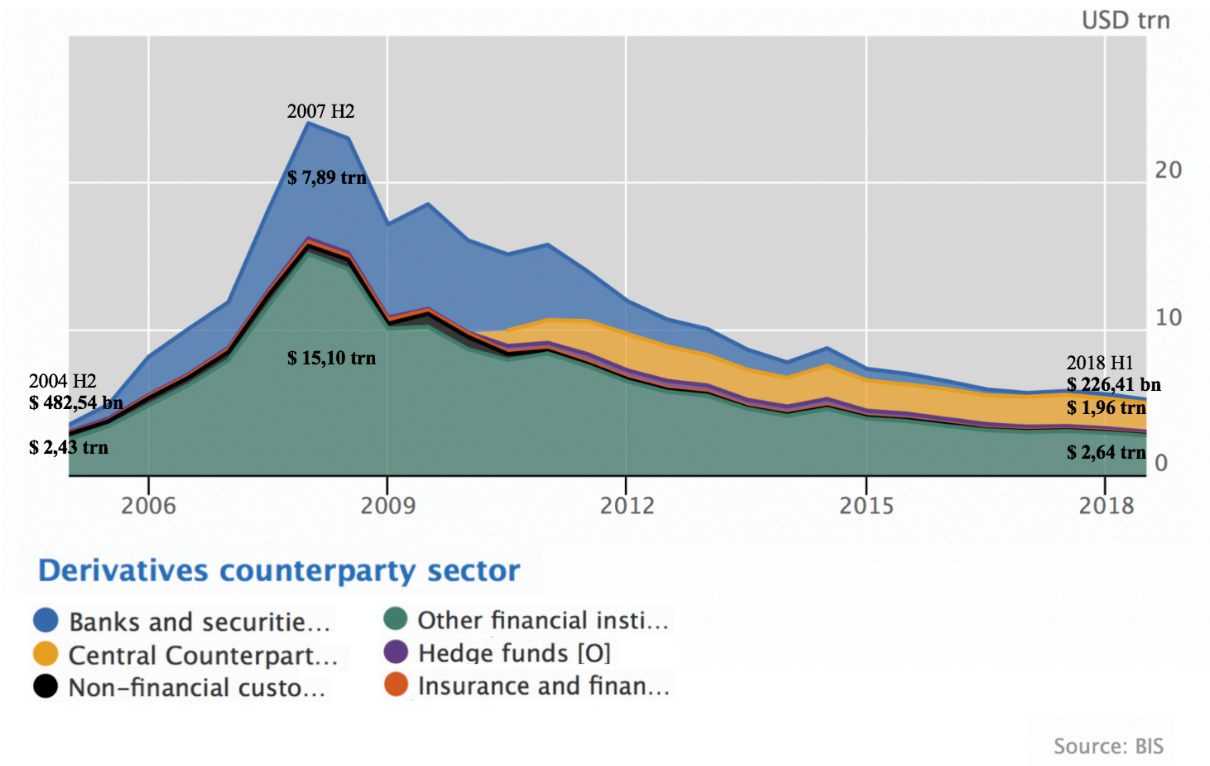

Figure 1.4: Notional amounts of Single–name CDS divided by sector outstanding.

Yet from a first look is evident that the market is highly concentrated: most trades relate to a few reference entities, which in turn account for a large share of gross notional amounts. Dealers occupy the lion's share of transactions and associated net and gross notional. Overall, the dealers have a small net/gross ratio, reflecting their intermediation role (ESRB–European Systemic Risk Board, 2016).

Specifically, over the life–cycle of the instrument the two main counterparties sectors are "Banks and securities firms" and "Other financial institution" even if in the after–crisis period, "Central Counterparties (CCPs)[6]" began a great component, mostly due to the wide regulation

[6] See paragraph 1.2.4.

issue. Regulation that deeply affected the CDS market, changing thus, the entity of the counterparties in the contracts. However, “Other financial institutions”, “Non–financial corporations”, as well as “Insurance and financial guaranty firms” are generally net buyers of protection.

Hence, from the end of the 1990s, banks have been, among the others, the largest buyers of credit protection and insurance companies are among the biggest sellers. This market has exploded with great importance and influence in financial markets.

1.2.4 Regulation

An in–depth in regulation is made necessary, particularly after the financial crisis, when the market started to realize that the deregulation of the Over the Counter (OTC) markets were a weak point for the negotiation of the instrument. For instance, the possibility to trade with a stranger, the absence of transparency, the shortcoming of regulation and protection pointed out the need to find some new rules of the game or other implementations that could help the market to give more guarantees and protection to counterparties.

Consequently, innovation in this direction have been made and the growth of the regulation becomes, indeed, a key factor in the changes in the CDS market, starting from the ISDA Master Agreement of 1999, which was updated in 2001–2002, in order to provide Over the Counter (OTC) counterparties with a fully documented, yet flexible, contract as a basis for negotiating the derivatives transactions; followed by a further standardization, in the post–crisis period, with the implementation of the CDS “Big Bang” and CDS “Small Bang” protocols in 2009 for the United State of America and for the European Union.

The primary objective of these new regulations was to bring alterations in the contract and trading conventions and particularly to improve the efficiency and transparency of the Credit Default Swap markets due to the fact that the CDS contracts are traded in Over the Counter markets.

One change of the “Big Bang” of April 2009 was the standardization of the coupon payments. Therefore, the fixed coupon payments for Single–name CDS were established to be both 100 and 500 basis points, whereby any difference relative to the running par spread would be settled through an upfront payment, which helped to equalise contracts referred to the same reference entity and make things more comparable.

It, also, allows Credit Default Swap contracts to have the Determinations Committees which make binding determinations in connection with credit and succession events, including whether or not to hold an auction to settle CDS contracts following the occurrence of the credit event.

Further harmonisation was made on the side of a default determination, again, in order to reduce the creation of disparity on similar contracts, for instance, to avoid that a certain credit event may trigger the payment in one case and may not in an analogous one, as reported by BIS in 2010. While the Small Bang protocol offered a second and last possibility for the parties to adhere to the Big Bang protocol, indeed by accepting the Small Bang, a party that did not adhere to the Big Bang will be deemed to have adhered also to the Big Bang one.

Despite these improvements in CDS' standardisation and the widespread use of risk–mitigation techniques such as compression, outstanding notional amounts from bilateral exposures were still large. For this reason, Credit Default Swaps represent an important source of counterparty risk.

Nowadays that type of risk is absorbed by CCPs and also several safety buffers have been put in place for reducing it, such as default funds, multiple levels of margin requirements, equity and reserve requirements for CCPs. Where CCP stands for "Central Counterparty Clearing", it is a corporate entity that reduces counterparty, operational, settlement, market, legal and default risk for traders. Acting as counterparty to buyers and sellers, CCP guarantees the terms of a trade even if one party defaults on the agreement. The Central Counterparty either clear and settle the trading between counterparties.

By the end of 2013, Credit Default Swap contracts with central clearing accounted for 26% of all gross notional amounts of CDS outstanding (data retrieved by the Bank for International Settlements).

Improvements in regulation did not stop at that point in time, hence new acts came into the picture.

Importantly, in 2010 the Dodd–Frank Act mandates that certain standard OTC derivatives must be traded on Swap Execution Facilities (SEFs). This went under the name of MAT mandate. (Riggs *et al.*, 2018). The main purpose was to restore public confidence on these types of instruments and markets.

The Dodd–Frank Act wanted by Obama, was created particularly for the American market which, following this law, became subject to various supervision and intervention by the SEC (Securities and Exchange Commission) and the CFTC (Commodity Futures Trading Commission).

Concerning Europe and according to EMIR, all EU–located legal persons (counterparties) entering into a derivative contract must report the details of that contract to a trade repository (TR) authorised by ESMA. Specifically, the authorised trade repositories are CME, DTCC, ICE[7], KDPW, Regis-TR and UnaVista Limited.

These six Trade Repositories provide daily data to over 60 institutions in the EU, which have access to the data pertaining to their respective jurisdiction.

The Depository Trust and Clearing Corporation (DTCC) is an American company that provides clearance, settlement and information services to financial markets. It offers a huge dataset of information, simplifying the complexities of data management across transaction types and asset classes, increasing transparency, mitigating risk and driving efficiencies for financial firms, as reported in the website. DTCC in March 2010, gave greater access to CDS data in order, indeed, to achieve more transparency although it still remains a flaw for Credit Default Swap.

1.3 Advantages and disadvantages of CDS

Given the complexity and the low level of transparency in OTC derivatives markets, Credit Default Swaps has represented a widely recognised source of systemic risk and still do it. In particular, the great and various use that has been made of the contract and the fact that the transaction in OTC markets are not so clear as it should, have let the world to be divided into two factions, those who believe CDS is a "good" instrument and others who even perceive it as one of the causes of the 2008' financial crisis.

Indeed, Augustin *et al.* in 2014 asserted that while the CDS' proponents defend them as efficient vehicles with which to transfer and manage credit risk as well as means to widen the investment opportunity set, their opponents denounce them as "poisonous", "toxic", "time bombs", "financial hydrogen bombs" or even "speculative bets" that influence government default.

[7] With approximately 4 million contracts cleared every day across multiple asset classes, ICE Clear Europe is one of the world's most diverse and leading clearing houses. It provides central counterparty clearing and risk management services for interest rate, equity index, agricultural and energy derivatives, as well as European credit default swaps (CDS). As part of ICE strategy to provide clearing services in the regulatory jurisdictions and time zones where you do business, they offer secure, capital-efficient clearing, risk management and physical delivery services through ICE Clear Europe. To help mitigate systemic risk and protect the interests of ICE's clearing members and customers, ICE Clear Europe holds $35 billion in its financial guarantee package (guarantee fund) and is regulated by the Bank of England in the U.K. and by the SEC and CFTC in the U.S.

Negotiation concluded with a phone call is just an example that makes reflect on how much of opacity there is behind the transaction in the Over the Counter market. This is scary since no one knows the exact conditions and quantity of each trade as soon as it occurs; the solution that the opponent sustain is a complete regulation, transparency of the instrument throughout the creation of regulated exchanges.

Actually, without knowing much of the CDS market, transaction and the great notional amount in circulation make thing even harder to understand, thus a trader no longer distinguishes where this huge amount is due to an increase of the spread because of the increase in the risk perceived or it is just a bubble.

A strategy applied to CDS that may result in a bubble and has been largely applied to the instrument is the so–called "Netting strategy[8]" is considered one of the cons for the instrument itself. Specifically, this practice consists of taking the risk by selling a CDS contract and, on the other hand, on protecting from the same risk by buying, meanwhile, a protection CDS; that procedure allows, the former seller (that becomes buyer in the second operation) to offset the risk (i.e. netting the position), in that way, he may earn something by charging a higher premium when it acts as seller of the protection and pay a lower premium as buyer of CDS. It's easy to understand that this procedure could possibly be repeated for an indefinite number of times, thus the person, or the entity, that has sold for last the CDS protection could, in turn, buy from another one a credit derivative protection and so on.

That strategy works until some of these netting operators' defaults, hence when he is no longer able to meet his obligation, at this point the chain breaks.

Particularly, this example shed light on one characteristic of the Credit Default Swap market, the interconnection that disrupt in any part of it and could cause ripple effects throughout the entire system.

Moreover, another unfavourable consequence of using Credit Default Swap perhaps is due to the intervention of government in the financial market. Specifically, the rescue of AIG from the Federal Reserve, the Germany providing bailout to the Hypo Real Estate or, even, Belgium, France and Luxemburg providing 150 € billion of guarantee for Dexia's debt, all this events and other, point out the governments' responses to financial crisis aim at supplying liquidity and at decreasing systemic risk in the market, which in turn should lower the CDS prices.

[8] For more detail visit: https://www.learningmarkets.com/netting-and-credit-default-swaps/

As emphases by Kamga *et al.* in 2017, yet noticed by Archarya *et al.* in 2010, these government interventions, on one hand, stabilize financial markets, but on the other hand, they allow the transmission of risk from the financial sector to sovereigns.

Chapter 2

2 Bank–Credit Default Swap relationship

We notice, from past studies, that Credit Default Swap positions are quite large compared to the direct credit exposure of the Credit Default Swap's reference entities and usually banks tend to sell more credit protection than what they acquire against counterparties in their loan, bond and securities portfolios, which is the opposite of what one would expect if the only reason to use that derivative contract were to hedge credit risk.

For these reasons, before getting into the detail of our empirical work, we want to present credit risk and the several uses of the instrument identified in the past, then focus on some of them that we adopt to carry on the analysis and, more, we want to review some evidence coming from past literature on analogous works.

2.1 Credit risk

Among all the possible motivation that could create difficulties to banks or, even, lead to a deterioration and defaults, there is one fundamental cause that has played and still play a key role. We are talking about credit risk. This is the reason why Credit Default Swap originally born: to hedge credit risk.

Credit risk is defined by the Basel Committee on Banking Supervision (BCBS) as "*the potential that a bank borrower, or counterparty, will fail to meet its payment obligations regarding the terms agreed with the bank. It includes both uncertainties involved in repayment of the bank's dues and repayment of dues on time*".[9]

It is calculated based on some borrower's characteristics in order to determine he/she's ability to repay the debt according with the terms agreed. For instance, to assess credit risk on a consumer loan, banks have to check out some borrower's specific feature like credit history,

[9] https://www.bis.org/publ/bcbs54.pdf

capacity to repay, capital that own, the loan's condition terms and, if present, the associated collateral.

Historically, during the subprime crisis, many banks made significant losses in the value of loans granted to high–risk borrowers. Indeed, at that time banks made loans to everybody, even to persons that were not able at all to repay the obligations.

Major banks all over the globe suffered similar losses due to incorrectly assessing the likelihood of default on mortgage payments. This inability to assess or respond correctly to credit risk resulted in companies and individuals around the world losing a lot of money.

Nobody can, in advance, know exactly who will default on obligations, in which amount and when it will occur but, despite the evident difficulties in assessing that, banks could manage credit risk by creating provisions at the time of disbursing loan.

Most of them are regulated by the capital requirement for credit risk, which establishes the portion of capital that banks need to keep as deposit in order to face possible failure in debt repayment from customers.

In particular, the first pillar of Basel III establishes that institutions shall at all times satisfy the following own funds requirements:

- Common Equity Tier 1 capital ratio of 4.5%;
- Tier 1 capital ratio of 6%;
- Total capital ratio of 8%.

expressed as a percentage of the total risk exposure amount.

The determinant of this risk is obviously to be found in the fundamentals of the subject or entity itself, in particular in its economic, financial and equity situation.

In that way one should be able to determine the repayment capacity and creditworthiness of the bank's counterparty in the daily transactions.

The measurement of credit risk is of fundamental importance for the formation of the price of a bond and there is various method to assess the risk in question. The most common indicators of creditworthiness can be divided into two main categories:

- Direct indicators;
- Indirect indicators.

Direct indicators are characterized by the proposition of an explicit and immediately perceptible representation of credit risk, the so–called rating.

The rating is a summary judgment assigned by the banks, either an internal rating and/or an external rating by specialized companies (i.e. the rating agencies), on the reliability of the borrower translated into an alphanumeric symbol referring to a specific scale of values divided by class.

The analysis is either quantitative and qualitative style in which various economic factors are taken into consideration, including: the prospect of future earnings and future cash flows, the capital structure, the debt characteristics, the level of liquidity, the situation in the country, the market situation, the industrial sector in which the company in question operates, the quality of the managerial class and other information.

Indirect indicators have completely different characteristics from those of direct indicators. In fact, these do not derive from any analytical assessment process of creditworthiness and, to the contrary, reflect the expectations of market operators, being an implicit measure of credit risk. They are identified with the prices of financial instruments whose pricing model reflects market assessments of the creditworthiness of the companies issuing the bonds.

Ascertained the relevance of this type of risk, banks have always to be prepared to face it. Thus, banks exploit Rating Agencies to help them self–establish the credit risk level of each counterparty.

In particular, banks may choose between two methodologies for calculating their capital requirement for credit risk:

- *The standardized approach*;
- *The IRB approach: foundation and advanced approach*.

Under the standardized approach the credit risk is enhanced by means of, first, a segmentation of exposures into seventeen types, then the use of ratings issued by export credit agencies (ECAs) or specialized external credit assessment institutions (ECAIs) recognized for this purpose by the supervisory authorities. Where with the ECAIs is intended the above cited rating agencies.

Whereby, the Internal Rating Based (IRB) approach is a more advanced approach that uses several variables for the estimation of the Probability of Default (PD) such as the LGD (Loss Given Default), EAD (Exposure At Default) and the Maturity,

Where for PD we intend the probability that a counterparty will default within a preestablished time horizon (generally one year); for LGD, the expected value of the ratio between the loss due to default and the amount of the exposure at time of default; for EAD, the value of on–balance and off–balance exposures and finally, for Maturity, the average, for a given exposure of the residual contractual maturities of the payments due, each weighted by its amount.

The IRB method may be divided into two approaches, the foundation and the advanced ones, which differ a little each other but both have the aim to get an estimation of the Probability of Default of the counterparty.

2.2 Rating Agencies

Rating Agencies are independent private companies committed to assess the creditworthiness of states, bonds and issuers active on the market with the aim to translate that assessment into a synthetic parameter that is easily understandable.

Albeit their diffusion around the world, the most important Rating Agencies are:

- Fitch Rating Ltd.;
- Moody’s Investor Service Inc.;
- Standard and Poor’s Financial Services LLC.

Bond credit–Rating Agencies, such as Moody's Investors Services and Fitch Ratings, evaluate the credit risks of thousands of corporate bond issuers and municipalities on an ongoing basis.

In fact, as preannounced, they translate their evaluation into an alphanumeric and generally understandable classification. For instance, Moody’s methodology to assess credit risk is reported as an example in the following figure.

In particular, the picture captures the part of the guidance they published in 2017 where Moody’s Investor Services explained how the build the grid with the alphanumeric evaluation. The one reported refers to how evaluate a manufacturing corporation and, as we can see form the picture, they divide the construction of the evaluation in different factors, each of them contributes with its weight to the formulation of the final rating, then based on the firm–specific characteristics, a class is assigned and then average out with the other factor’s assignments.

2.2.1 Moody’s example

How We Assess it For the Grid

In assessing this factor, we consider the company’s relative exposure to the volatility of industry cycles, the competitive landscape and the threat posed by possible new entrants or technological change. We consider a firm’s market share for its key products, the sustainability of its market position, its competitive advantages and their likely durability, and the degree to which its products or services are differentiated. Scoring of this factor also considers our view of each firm’s cost position and its ability to control its costs. The extent to which the company can pass through raw material costs is considered.

We do not expect a given company to match exactly the attributes listed in a given rating category. We score this factor based on the best fit across the various measures. However, certain weaknesses will tend to limit the scoring level. In particular, a reliance on a small number of operating locations is likely to limit the rating to the B or Caa rating category as operating risk in these cases will be very high. Companies with a single or only a few production sites face a higher probability of having output and profitability being impacted by strikes, equipment failures, power outages and other operating problems. Similarly, these firms are likely to have limited product diversity and end-market diversity, thereby negatively impacting their stability.

Factor 1: Business Profile (20%)

Sub-Factor	Sub-factor Weight	Aaa	Aa	A	Baa	Ba	B	Caa	Ca
Business profile	20%	Expected volatility in results is almost non-existent. Supported by a commanding market position, entrenched cost effectiveness, technology advantages and a well-balanced global reach.	Very low expected volatility in results. Supported by a deeply entrenched and leading market position that is highly defensible through cost effectiveness and technology leadership with global exposure.	Low expected volatility in results. Supported by a strong market position in its relevant market, demonstrated and sustainable competitive advantages, insulation from raw material cost fluctuations, and solid diversity characteristics.	Moderate expected volatility in results. Supported by a solid market position in its most important geographic or product markets. Is vertically integrated or can pass-through the majority of its costs. Good diversity characteristics provide a buffer against sudden/ unexpected shifts in demand.	Products are largely undifferentiated and the marketplace highly competitive, exposing company to periods of heightened volatility. Such exposure is tempered by an established market position, favorable costs, an ability to pass-through raw material costs, and fair diversity characteristics including modest operational concentration.	Products are undifferentiated , competition is intense and customers price sensitive, making results highly volatile. Company does not have advantageous cost profile or other competitive advantage to mitigate. High operational concentration.	Results are expected to be extremely volatile. Company has modest market presence, few competitive advantages and may have above-average costs. Very high operational concentration (1 or 2 locations).	Expected to have highly volatile cash flow generation, a single product line sold to few customers for a single use, an insignificant market position with many large competitors, concentrated exposure to a small cyclical market and uncertain demand, no pricing power, and a single operating site that has an uncompetitive cost structure. Permanent structural and technological disadvantages.

Figure 2.1: How Moody’s Investor Service assess its grid.

Source: Moody’s guideline

Overall, ratings are traditionally classified into two categories (excluding default):

I. Investment grade;

II. Speculative grade.

Investment grade securities are those with rating BBB- or better, i.e. the safest securities. Speculative grade securities are those below BBB-, also known as "high yield" or "junk".[10]

Figure 2.2 reports the rating class for the major three Rating Agencies.

	Moody's	S&P	Fitch
Investment grade	AAA	AAA	AAA
	Aa	AA	AA
	A	A	A
	Baa	BBB	BBB
Speculative grade	Ba	BB	BB
	B	B	B
	Caa	CCC	CCC
	Ca	CC	CC
	C	C	C
Default	D	D	D

Figure 2.2: Issuer and issue of rating class.

Agencies often modify ratings within the same rating class to provide a better definition of relative credit quality: for example, Moody's modifies the Baa category into Baa1, Baa2, and Baa3. Standard and Poor and Fitch modify the BBB class into BBB+, BBB and BBB-. Similar modifications are applied to the other classes.

Depending on the rating class assigned, for example a risk–averse investor may opt to buy a AAA–rated municipal bond. In contrast, a risk–seeking investor may buy a bond with a lower rating in exchange for potentially higher returns.

[10] Iannotta G. (2010). Investment Banking: a guide to underwriting and advisory services, Springer Heidelberg Dordrecht London New York.

2.3 Literature hypotheses

Ones is ascertained how to calculate credit risk, banks have to face it. One possibility, as we said several times, is the Credit Default Swap. It should be used, at least in theory, as hedging instrument in order to deal with this type of risk. The problem, following the past literature, is that, as opposed as we expect, the instrument is used for the most disparate motives and only sometimes its original intention is exploited.

We describe all the several uses that have been made of the instrument by studying past literature on the theme and then we focus only a bit here, but more in the following Chapter, in particular on the ones we decided to analyze.

2.3.1 Hypothesis 1: Credit enhancement

Under the credit enhancement hypothesis, banks can offer credit support in transactions they underwrite, as the ability to hedge through CDS can increase the supply of credit to firms and other counterparties by making corporate debts more attractive to a broad group of investors that are unwilling to hold credit risk. More specifically, the credit enhancement hypothesis predicts that the amount of Credit Default Swap protection that a bank has sold on a counterparty is positively correlated with its lending exposure to that counterparty[11].

Results 1

Minton *et al.* (2008) pointed out this hypothesis and they found support in their work. Their results show that the coefficient they called "has lending exposure", meaning that a bank has an exposure toward a reference entity, is positive and statistically significant in all their specifications. This positive coefficient suggests that banks with syndicated lending exposure to a counterparty tend to sell more Credit Default Swap protection on this counterparty compared with banks without such exposures.

[11] Minton B. A., Stulz R. and Williamson R. (2008). How Much Do Banks Use Credit Derivatives to Hedge Loans?, Springer, J Finan Serv Res 35:1–31.

Consequently, this result provides supporting evidence for the credit enhancement hypothesis, as shown in Figure 2.3.

	(1)	(2)	(3)	(4)
Has lending exposure	13.712^{***}	11.026^{***}	10.976^{***}	11.426^{***}
	[3.577]	[3.714]	[3.691]	[3.670]
Agent lender		9.666^{**}	9.269^{**}	8.961^{**}
		[4.219]	[4.166]	[4.163]
Bank RBCR			3.556^{***}	3.540^{***}
			[0.554]	[0.552]
Bank wholesale funding ratio			-6.693^{***}	-6.725^{***}
			[0.623]	[0.621]
Bank ROA			12.213^{***}	12.020^{***}
			[2.405]	[2.403]
Bank NPA ratio			-23.880^{***}	-24.084^{***}
			[2.749]	[2.744]
Bank size			0.069^{***}	0.070^{***}
			[0.022]	[0.022]
Firm investment grade				-9.471
				[11.482]
Firm has credit rating				-13.092
				[49.216]
Firm stock return				-0.044
				[0.041]
Firm distance-to-default				0.074
				[0.659]

Figure 2.3: Summary results of the regression to test the credit enhancement hypothesis.

Source: Minton *et al.* (2008)

2.3.2 Hypothesis 2: Relationship banking hypothesis

Even in this case we exploit the studied made by Minton *et al.* (2008) on that relationship.

This hypothesis want to examine whether the preexisting relationship between a bank and a counterparty affects how the bank buys or sells Credit Default Swaps on that counterparty.

In their contest, i.e. analyzing syndicated loans, they construct two variables to measure the banking relationship.

The first variable is “agent lender”, a dummy variable used to examine if a firm’s agent lender is different from other lenders when buying and selling Credit Default Swap on a firm. The second variable, “lender–borrower utilization ratio”, calculates the total amount that a firm has already borrowed from the bank divided by the bank’s total lending commitments to that firm. A high utilization ratio indicates that the firm relies heavily on the bank. The lender–

borrower utilization ratio thus provides another measure of the banking relationship between a bank and a firm.[12]

Results 2

The coefficient of “agent lender” is positive and statistically significant in regressions of bought and net Credit Default Swap suggesting that a bank tends to buy more Credit Default Swap protection on a firm if it is the agent of that firm. In addition, the coefficient of “agent lender” is also positive in all regressions of sold CDS positions and is statistically significant in most regressions, indicating that a firm’s agent lender also tends to sell more CDS protection on that firm.

Finally, the coefficient of “lender–borrower utilization ratio” is negative and statistically significant, implying that a bank tends to refrain from buying or selling Credit Default Swap on a firm if that firm relies heavily on the bank for its banking needs. Overall, they find mixed evidence for the relationship banking hypothesis. Although a firm’s agent lender tends to buy more Credit Default Swap protection on that firm, they also find that banks refrain from buying or selling Credit Default Swap on firms that rely heavily on them for banking.

2.3.3 Hypothesis 3: Firm risk

Another hypothesis studied is that, other thing being equal, banks are more likely to hedge their credit exposures when the counterparty is a riskier one (Aldasoro *et al.,* 2017).

They use as a proxy of the firm’s riskiness their 5 year Credit Default Swap market spreads. The idea that exposures to riskier firms are more likely to be hedged seems intuitive.

Thus, essentially this hypothesis argue that banks insure a larger share of their exposure to relatively riskier counterparty.[13]

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[12] Minton B. A., Stulz R. and Williamson R. (2008). How Much Do Banks Use Credit Derivatives to Hedge Loans?, Springer, J Finan Serv Res 35:1–31.

[13] Aldasoro I. and Barth A. (2017). Syndicated loans and CDS positioning, BIS Working Papers, Monetary and Economic Department, No. 679, December.

In line with the expectation of the hypothesis their result pointed out that banks in their sample are more likely to hedge their credit risk exposure toward riskier counterparty. Indeed, the coefficient they create (which we will use forward in the analysis) the "Uninsured Loan Ratio", i.e. the portion of the loan that remains uninsured by a Credit Default Swap contract, is smaller, the largest is the market CDS quote of the counterparty. This, in fact, suggests that banks insure more the riskier is the exposure. Figure 2.4 reports this evidence and the variable $CDS_{j,t-1}$ stands for the lagged CDS market quotes of the counterparty.

	(1)	(2)	(3)	(4)
$CDS_{j,t-1}$	-0.000**	-0.000	-0.000**	-0.000*
	(-2.131)	(-1.403)	(-2.463)	(-1.964)
$IMA_{i,t}$		-0.008***		-0.006***
		(-7.649)		(-6.153)
R^2	0.280	0.295	0.299	0.308
N	90800	90800	77918	77918
Sample	$S3$	$S3$	$S4$	$S4$
Bank controls	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓

OLS regressions for Equation (3). The dependent variable is the ULR_{ijt} defined in (2). Bank controls include: Size (log of total assets), wholesale funding to asset ratio, TIER1 ratio, leverage (total assets over equity) and return on assets. All variables are lagged by one period except for $IMA_{i,t}$. $CDS_{j,t-1}$ stands for the lagged CDS quote of firm j. $IMA_{i,t}$ stands for the index market activity defined above. t-statistics are given in parentheses; SE are clustered at the time level. ***, **, * indicate significance at the 1%, 5% and 10% levels.

Figure 2.4: Example of past literature result.

Source: Aldasoro *et al.* (2017)

2.3.4 Hypothesis 4: Private information hypothesis

This section reflects on the hypothesis that a bank's private information about the credit quality of the counterparty will affect the trading on Credit Default Swaps toward that counterparty.

The authors of the papers of the first and second hypothesis just presented, also consider that case by examining the coefficients of two variables that reflect the internal credit ratings that banks, with their means, do on counterparties: "Rating: special mention" and "Rating: classified".

Where "Rating: special mention" is a dummy and means that the assets where is posed the special mention, has a potential weakness that deserve management's close attention. If left uncorrected, these potential weaknesses may result in further deterioration of the repayment prospects or in the institutions' credit position in the future. Special mention assets are not adversely classified and do not expose institutions to sufficient risk to warrant adverse classification.

On the contrary "Rating: classified" is an indicator that equals 1 if any facility of the firm has a classified rating (substandard, doubtful or loss). Which means we are in front of a risky asset.[14]

Result 4

The coefficient "Rating: classified" is positive and statistically significant in their regression. These results indicate that banks tend to acquire and sell more Credit Default Swap protection on a counterparty that results in the internal rating as is deteriorating its credit quality.

On the contrary, considering the regression as net Credit Default Swap position, no longer the single position buy or sell but the two together, none of the coefficients of "Rating: special mention" and "Rating: classified" are statistically significant.

Overall, this result is somewhat puzzling and may be due to the reputation risk arising from conflict of interest.

Another aspect to take into consideration is that the agent lender, i.e. the variable presented in the outlined hypothesis above, may has superior private information about the borrower. In

[14] Meaning of the variables are presented in the appendix of Minton et al. (2008).

addition, the lender–borrower utilization ratio may also contain private information about a borrower. Therefore, the coefficients of these variables may also reflect the effects of a bank's private information about the counterparty.

2.3.5 Hypothesis 5: Cross–border hedging

An interesting feature analyzed in the past literature is the cross–border nature of both lending and Credit Default Swap data.

It is sensible to believe that, after controlling for borrower specific characteristics, cross–border, with the respect to the domestic loans, are more likely to be insured.

Let's consider, for instance, a situation where the bank has to grant a loan to two identical counterparties, one located in the same country of the bank and the other located in another country.

Maybe for a sort of sentiment of familiarity, of somewhat that we perceived as known, we expect that the first loan is less likely to be insured, or at least insured for a little fraction, than the second one. This can be due for instance to more uncertainties related to cross–border lending, little knowledge of the operations and regulation that apply to the counterparty's state of origin, less ability to monitor, less strength of relationship lending and other motivations like these.

Result 5

Results for this regression are peculiar. Indeed, the domestic loan dummy, turns out to be a negative and significant coefficient.

This implies that, controlling for a series of bank characteristics and different fixed effects, banks are more likely to hedge their domestic loans relative to similar foreign loans, i.e. the opposite of what we expected from this type of regression.

Thus, comparing a bank lending to two identical counterparties (including the same level of riskiness), the authors find that the loan to the domestic firm is hedged to a larger extent with the respect to loans granted to foreign counterparties. This could point out, as the law of diversifying portfolio does, that banks attempt to overcome their home bias, diversifying out, thus granting loans abroad.

2.3.6 Hypothesis 6: Asymmetric information externalities

When talking about syndicated loans is possible to encounter also problems of asymmetric information and Aldasoro *et al.* (2017) pointed it out. The structure of syndicated loans, where a lead arranger bank is in charge of establishing the relation with the borrower, negotiating and setting up the loan contract, monitoring, screening and other mansion that are part of their relationship, naturally leads to such problems.

As we considered in the fourth hypothesis the agent has sensible information and thereby have incentives to misrepresent the quality of the loan, creating in this way adverse selection problem.

Furthermore, when retaining smaller shares of the loan, lead arrangers also have an incentive to underperform in the monitoring of the loan, i.e. a moral hazard concern explores issues of asymmetric information between lenders and borrowers in the syndicated loan market and finds that, consistent with moral hazard concerns, lead arrangers retain a larger share of the loan.

This can be a way to mitigate asymmetric information concerns by providing direct evidence of a commitment to monitor via skin in the game.

However, Parlour C. A. and Winton A. (2013), noted that a bank after making a loan, check out if the loan needs contract enforcement, such as monitoring; it also decides whether to lay off credit risk in order to release costly capital.

Actually, a bank can lay off credit risk by either selling the loan or by buying insurance through a Credit Default Swap.

With a Credit Default Swap, the originating bank retains the loan's control rights but no longer has an incentive to monitor.

To the contrary, with loan sales, control rights pass to the buyer of the loan, who can then monitor, albeit in a less–informed manner.[15]

[15] Parlour C. A. and Winton, A. (2013). Laying off credit risk: Loan sales versus credit default swaps. Journal of Financial Economics, 107:25{45.

Given the Over The Counter (OTC) nature of the market, lead arrangers may thus have an incentive to tap this market, anonymously shed the credit risk arising from their loan share and, thereby, void the informational value of their loan share commitment.

However, such massive OTC protection buying, easily may lead to exacerbate information asymmetry problems. To summarize, this hypothesis they want to test if lead arrangers buying more protection, can have the deteriorating effect of increase problems of asymmetric information.

Result 6

Authors find negative and significant coefficient for the lead arranger dummy. In line with the hypothesis they find, by comparing a lead–arranger bank with one that it is not, the lead–arranger tends to acquire more net protection.

However, the fact that in OTC all happen anonymously it should allow at the same time to “anonymously” reduce credit risk.

Regulatory capital relief and hedging hypothesis

Finally, with this last two hypotheses we get into our main focus. Indeed, this two represent the hypotheses we want to test in the empirical part of this work, and we will go through them, explaining how we implement them in the next Chapter, here instead, we report how papers from which we get inspiration, worked on the theme.

2.3.7 Hypothesis 7: Regulatory capital relief

The regulatory capital relief hypothesis postulates that banks create deals such that allow them to reduce the capital needed in order to satisfy the regulators. In particular, Credit Default Swap bought and net position CDS (i.e. sold minus bought), are negatively correlated with its regulatory capital ratio.

The main indicator of the regulatory capital ratio is the Tier 1, that as presented above, indicates the best quality capital that banks have as deposit.

Hedging through Credit Default Swap, actually, has a countereffect that is it will increase a bank's regulatory capital ratio. In other words, we face a reverse causality problem between the net CDS position and the regulatory capital ratio, since the two contemporaneously affect one the other.

Although, is less likely that a change in the Credit Default Swap position on a single counterparty will significantly affect a bank's capital ratio the paper, and also us in our paper, solve the problem by considering the dependent variable measured at time t and the explanatory variables measured at time $t-1$, in this way the reverse causality is not a concern.

In any case, there is a limitation in the use of this type of strategy since if the bank does not have any lending exposure toward a specific counterparty, for instance "Company A", it cannot use the Credit Default Swap instrument bought on the Company A to obtain regulatory capital relief. In this situation no shift in the internal rating of that company is made, thus there couldn't be a reduction, in favor of the bank, in the capital needed to insure from the credit risk that the company can carry with it.

For this reason, Minton *et al.* (2008) exclude, in their work, observations of all bank–counterparty pairs in which the bank has no lending exposure.

Result 7

Consistently, with the regulatory capital relief hypothesis, they find that banks with lower regulatory capital ratios tend to buy more Credit Default Swap protection.[16]

Completely different are the result obtained in Aldasoro *et al.* (2017) that use, instead, a broad European sample and find out no support for the capital relief hypothesis in their regression, whereby, Minton *et al.* (2008) have used an American sample.

[16] Minton B. A., Stulz R. and Williamson R. (2008).

2.3.8 Hypothesis 8: Hedging hypothesis

Under the hedging hypothesis, one would expect that a bank's amount of CDS bought and the net positions on them, be positively correlated with the bank's lending exposure to that counterparty. Indeed, the higher is the exposure, thereby the risk coming from that counterparty, the more banks should be worried about that and attempts to hedge their positions.

The estimation method in Minton *et al.* (2008) is the Ordinary Least Squares (OLS) with bank, firm, and time fixed effects. In their analysis they both consider bank with and without a lending exposure versus counterparty (for them are all firms).

The dependent variable is "bought CDS position", which is the notional amount of CDS protection that a bank has bought on a firm at time t. The explanatory variables are observed at previous time, i.e. at time $t-1$ and the key one for this type of regression is "has lending exposure". Which is equal to 1 if the bank was a lender in the period considered to the firm and zero otherwise.

All their regressions include bank fixed effects to control for unobserved time–invariant bank–level factors, firm fixed effects to control for unobserved time–invariant firm–level factors, and time fixed effects to control for the combined effects of observed and unobserved macroeconomic factors.

Result 8

Testing this hypothesis, they find mixed evidence. Banks with lending exposures to a counterparty tend to buy and sell more Credit Default Swap on that counterparty, but there is no significant difference in net Credit Default Swap positions on a specific counterparty between banks that have or do not have a lending exposure. Moreover, counterintuitively, the net notional amount of Credit Default Swap protection that a bank has bought on a firm covers only a tiny fraction of its lending exposure to that firm, instead as explained in presenting the hypothesis, a bank with a higher exposure should, in theory, be more protected from that counterparty credit risk.

Also, Hasan and Wu in 2016 studied this phenomenon and in that case the coefficient of lending exposure turns out to be positive and statistically significant in all regressions made, suggesting that banks with higher lending exposures to a counterparty, tend to have higher net Credit Default Swap positions on that firm. Although this positive coefficient, which is consistent with the hedging hypothesis, also in that case, its magnitude is very small.

Chapter 3

3 Data

In this Chapter, the empirical results are going to be presented and analyzed, considering both the two main strategies: hedging and capital relief instrument. We make comparison of different results depending on the type of the specifications done.

3.1 Objective

Our analysis aims to obtain insights regarding the motivation of the bank to hedge or speculate and to relief capital from the mandatory requirements imposed by the capital regulators. In particular, constructing our dataset we want to get an idea of how banks exploit the renowned Credit Default Swap instrument in their businesses. To clear off correlation from third factors, we apply panel regressions and a series of Fixed effects (i.e. Within Group and Between Effect) and Random Effects model that allow us to control for time–varying bank and reference entity–specific characteristics.

3.2 Dataset

We create our dataset by combining different sources and match them by hand on an Excel file. We can split into three macro–argument the type of information that we need to conduct our analysis. First, The CDS notional amounts that banks buy and sell over the time–span considered; second, the size of the loans provided to their customer, either corporates and other banks loans; third, general bank–specific information such as Tier 1 ratio, performance and size.

Our sample is a country–specific dataset, focused on Italy, it contains eight major banks which are the results of an accurate selection. Indeed, we exclude all the non–CDS active banks and the ones for which, at least at the time of the collection of the data, some information needed was not available.

The eight banks are:

⇒ Intesa Sanpaolo;

⇒ UniCredit S.p.A.;

⇒ UBI Banca;

⇒ Monte dei Paschi di Siena;

⇒ Banca Nazionale del Lavoro;

⇒ Banco Popolare di Milano;

⇒ Mediobanca S.p.A.;

⇒ BPER Banca.

3.2.1 Loans and bonds

We retrieve data for "Due from banks" (loans given to other banks) reading year–by–year our bank's balance sheets; more, whenever possible, we exploit the dataset Thomson Reuters Eikon which provides the division for segments of activity for each bank and specify, among the loans to customers, the amount referred to corporate loans, otherwise if not specified, we source by hand on the Footnotes in Part L; lastly, a bit more complicated, is quantify the magnitude of government bonds the banks buy to finance the Italian debt.

In that case, analyzing carefully the annual reports we find out this type of information reported in Part B of the Footnotes under the captions "Financial assets held for trading", "Financial assets designated at fair value", "Financial assets measured at amortized cost" and "Hedging derivatives" in the breakdown by borrower/issuer we isolate only the government bonds and sum up for each bank and year the four captions.

Every single caption report under points 1.a. and 1.b. debt securities versus government, central banks and public administration, except for year 2018 where we exclude point 1.a. because it becomes only debt security versus central banks.

Further, we assume that all values reported under these captions, refer to Italy and Italian government bonds so that we could even find a third type of exposure for which a protection instrument is relevant.

One feature, that is worth noting here, is that we move from the Banking book (as for data about credit from banks and corporates) to the Trading book for collecting data concerning the relationship between Italian banks and sovereign.

The table reports, as an example, the summarized amounts in thousands of euro for Intesa Sanpaolo.

		NOTIONAL AMOUNT					
		2018	2017	2016	2015	2014	2013
INTESA	**LOAN**						
	Counterparty						
	Government bonds	58.627.000,0	171.092.000,0	125.736.000,0	118.760.000,0	110.988.000,0	111.158.000,0
	Other banks	69.307.000,0	72.057.000,0	53.146.000,0	34.445.000,0	31.372.000,0	26.448.000,0
	Corporates	110.742.000,0	109.399.000,0	98.183.000,0	89.691.000,0	82.385.000,0	90.907.000,0

Table 3.1: Sample of loan's notional amount for Intesa Sanpaolo.

3.2.2 CDS notional amounts

We obtain Credit Default Swap notional amounts data from the bank's annual report, we search on Part E of the Footnotes for each bank and year. In this way we have information on the amount of Credit Default Swap (CDS) bought from any protection seller and sold to any protection buyer, but no information is given regarding who is the reference entity toward which the protection is bought or sold.

We solve this problem by making an assumption: we know the amount of the protection that each bank buy or sell (from/to central counterparty, banks, other financial institution and corporates), we know the amount of the loans given to other banks, corporate and sovereign (although when we talk about sovereign we refer to government bonds, not loans, as specified above), the only missing information is which are the reference entities toward which the protection is needed, thus we assume that the amount bought and sold can be divided, proportionally to the size of the corresponding loans, between sovereign, banks and corporate, respectively.

Indeed, for instance, looking at Intesa Sanpaolo, as the Table 3.2 shows, it has bought 20˙978€ millions of CDS, in 2018, from Central Counterparty (CCP), as reported in the

Footnotes, then we assume that $\frac{3}{8}$ is used as protection from the reference entities "state" and "corporate", respectively; $\frac{1}{4}$ for the reference entity "banks". The proportions are in line with the amount of exposure versus state, banks and corporate. They may differ from one bank to the other.

			NOTIONAL AMOUNT			
			2018		2017	
INTESA SANPAOLO	PROTECTION BOUGHT FROM					
	Central counterparty		**20.978.000,0**		**146.000,0**	
		STATE		7.866.750,0		54.750,0
		BANKS		5.244.500,0		36.500,0
		CORPORATE		7.866.750,0		54.750,0
	Banks		**22.015.000,0**		**23.578.000,0**	
		STATE		8.255.625,0		8.841.750,0
		BANKS		5.503.750,0		5.894.500,0
		CORPORATE		8.255.625,0		8.841.750,0
	Other financial institutions		**9.597.000,0**		**21.037.000,0**	
		STATE		3.598.875,0		7.888.875,0
		BANKS		2.399.250,0		5.259.250,0
		CORPORATE		3.598.875,0		7.888.875,0
	Corporates		**168.000,0**		**-**	
		STATE		63.000,0		-
		BANKS		42.000,0		-
		CORPORATE		63.000,0		-
	Check tot		*52.758.000,0*		*44.761.000,0*	
	PROTECTION SOLD TO					
	Central counterparty		**21.150.000,0**		**-**	
		STATE		7.931.250,0		-
		BANKS		5.287.500,0		-
		CORPORATE		7.931.250,0		-
	Banks		**20.605.000,0**		**19.865.000,0**	
		STATE		7.726.875,0		7.449.375,0
		BANKS		5.151.250,0		4.966.250,0
		CORPORATE		7.726.875,0		7.449.375,0
	Other financial institutions		**10.334.000,0**		**21.771.000,0**	
		STATE		3.875.250,0		8.164.125,0
		BANKS		2.583.500,0		5.442.750,0
		CORPORATE		3.875.250,0		8.164.125,0
	Corporates		**-**		**-**	
		STATE		-		-
		BANKS		-		-
		CORPORATE		-		-
	Check tot		*52.089.000,0*		*41.636.000,0*	

Table 3.2: Sample of CDS protection bought and sold for Intesa Sanpaolo for years 2017–2018.

3.2.3 Bank–specific information

Lastly, general information on bank's performances, size (approximated as the natural logarithm of the total assets)[17], ROA (Return on Assets, i.e. Net Income/Total Assets), Tier 1

[17] See Aldasoro I. and Barth A. (2017).

ratio, Leverage and other indicators, are obtained from annual report; if not directly available, compute them by hand.

Sometimes we exploit also information given by Thomson Reuters Eikon since it proposes some useful segmentation that we can use without further modification, e.g. the Tier 1 ratio is directly readable in there.

3.3 Methodology

3.3.1 Hypothesis

With the structure of the data in mind, we now recall and formulate the two main hypotheses that will be tested in the empirical analysis. These represent the research question of the study: Is a CDS used by banks as hedge or capital relief instrument?

3.3.1.1 Hypothesis 1: Hedging instrument

Our first hypothesis explores the most basic dimension relating to bank's health and its hedging behavior. In particular, we posit that weaker banks will on average insure a smaller share of their exposures. In our analysis, weaker banks will be those scoring relatively poorly on risk (highly leveraged banks) and profitability (low return on assets). Cast in this way, the hypothesis can also be linked to a charter value argument, even though we do not actually compute charter values for the banks in our sample.

More precisely, lower charter values (associated to weaker banks) decrease the incentives for a bank to ensure its lending business, i.e. the circumstance that the threat of losing future rents is less severe might act as a deterrent to insure loan activities. Hypothesis 1 summarizes this conjecture.

⇒ Hypothesis 1 (Hedging behavior): Ceteris paribus, weaker (stronger) banks tend to insure less (more).

3.3.1.2 Hypothesis 2: Capital relief

In our second hypothesis, we argue that, under certain conditions, bank capital regulation allows banks to reduce the risk weights attached to some of their credit risk exposures by buying protection from a counterparty that has a better credit rating than the entity to which the bank is originally exposed to. That is, Credit Default Swaps can be used for capital relief purposes. Indeed, this instrument acts as a mitigator exploited by banks in order to, artificially, satisfy the mandatory requirements by the regulator.

Discover this type of strategies is pretty hard but under this capital relief hypothesis, we expect that banks that are in a weaker position in terms of their risk–weighted regulatory capital ratios (i.e. Tier 1 ratio) have a greater incentive than their better capitalized peers to buy Credit Default Swap protection on their credit risk exposures in order to lower the capital requirement implied by their lending portfolios.

We decide to use the Tier 1 capital ratio (Tier 1 Capital/RWA) for measuring the bank capital adequacy, because compared with the total capital which, instead, includes reserves, general provisions and subordinated term debt, Tier 1 capital is a better measure of core capital and thus a core measure of a bank's financial strength.

As in Hasan *et al.* (2016) and Aldasoro *et al.* (2017) this hypothesis requires a negative correlation between net CDS positions (which is the difference between instrument acquired and sold) and the regulatory capital. This hypothesis also speaks to the vast literature on the relationship between bank capital and risk aversion.

⇒ Hypothesis 2 (Capital relief): Ceteris paribus, banks with lower regulatory capital, i.e. low percentage of Tier 1 ratios have stronger incentives to hedge their credit risk exposures for capital relief purposes, in order to comply with the mandatory regulation about capital requirements.

3.3.2 Empirical approach

Dependent variable

Our empirical work tries to explain the portion of loans of bank i to counterparty j (where j could be firm, state or other banks) that remains uninsured at time t (therefore ULR_{ijt}, stands for Uninsured Loan Ratio). In order to calculate this share, we first organize the data by bank, year and protection bought and sold, then we calculate the net notional amount of CDS protection on reference entity j (where it is again j = corporate, government and other banks) by bank i at time t as the difference between the sum of bank i's Credit Default Swap protection bought on reference entity j from any protection seller k (k =central counterparty, banks, other financial institution and corporate) and the aggregate amount of bank i 's Credit Default Swap protection sold on reference entity j to any protection buyer k.

Thus,

$$NET\ NOTIONAL\ CDS\ HOLDINGS_{ijt} = \sum_k NOTIONAL\ CDS\ BOUGHT_{ij,k} - \sum_k NOTIONAL\ CDS\ SOLD_{ij,k}$$

Now we have a measure of the net position on the CDS for every single bank on the specific reference entity.

Subsequently, obtain the variable Uninsured Loan Ratio as the difference between the loans from bank i to the reference entity j at time t and the new measure just calculated, the net notional CDS holdings of bank i to the reference entity j at time t, then normalized for the corresponding loan amount.

$$ULR_{ijt} = \frac{LOAN\ HOLDING_{ijt} - NET\ NOTIONAL\ CDS\ HOLDINGS_{ijt}}{LOAN\ HOLDING_{ijt}}$$

If $ULR_{ijt} = 1$, then bank i does not buy or sell (on net) protection on reference entity j at time t.

Values of ULR_{ijt} grater than 1 indicate that the bank is doubling–up on its credit risk exposure, whereas value of ULR_{ijt} smaller than 1 indicate the bank is (at least partly) hedging the loan exposure.

ULR_{ijt} can indeed take negative values as Figure 3.1 shows the example of our sample case, which would imply over–insurance on the part of the bank (i.e. buy net protection on reference entity j over and above the loan exposure among the three different counterparties).

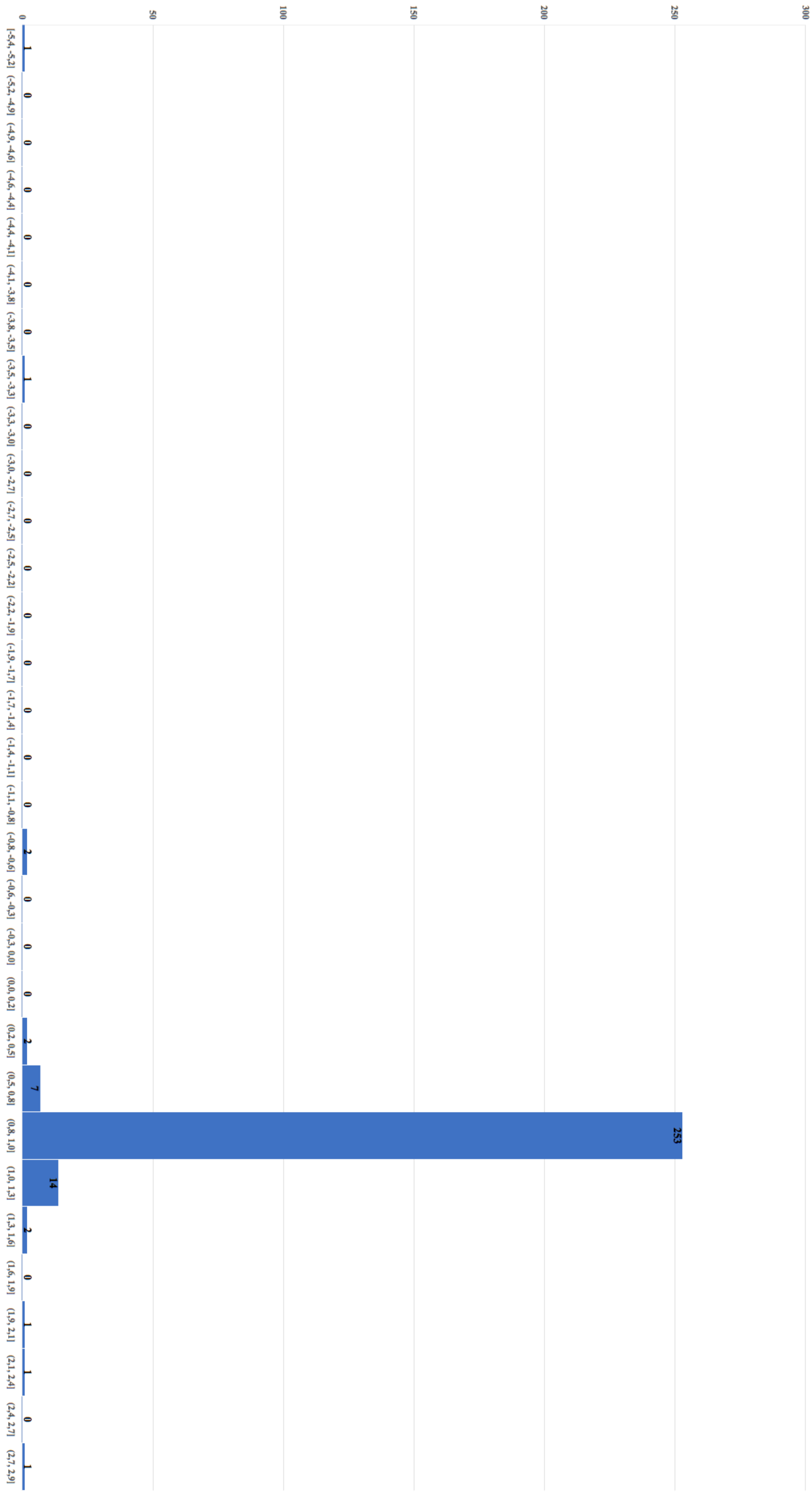


Figure 3.1: Relative frequency of the uninsured loan ratio (ULR).

3.4 Model

We test the two hypotheses in a regression where we infer the Uninsured Loan Ratio connecting bank i with the reference entity j at time t to a function of bank characteristic, at the same time, controlling for bank–specific and reference entity feature. We also control for bank–specific time–constant effects.

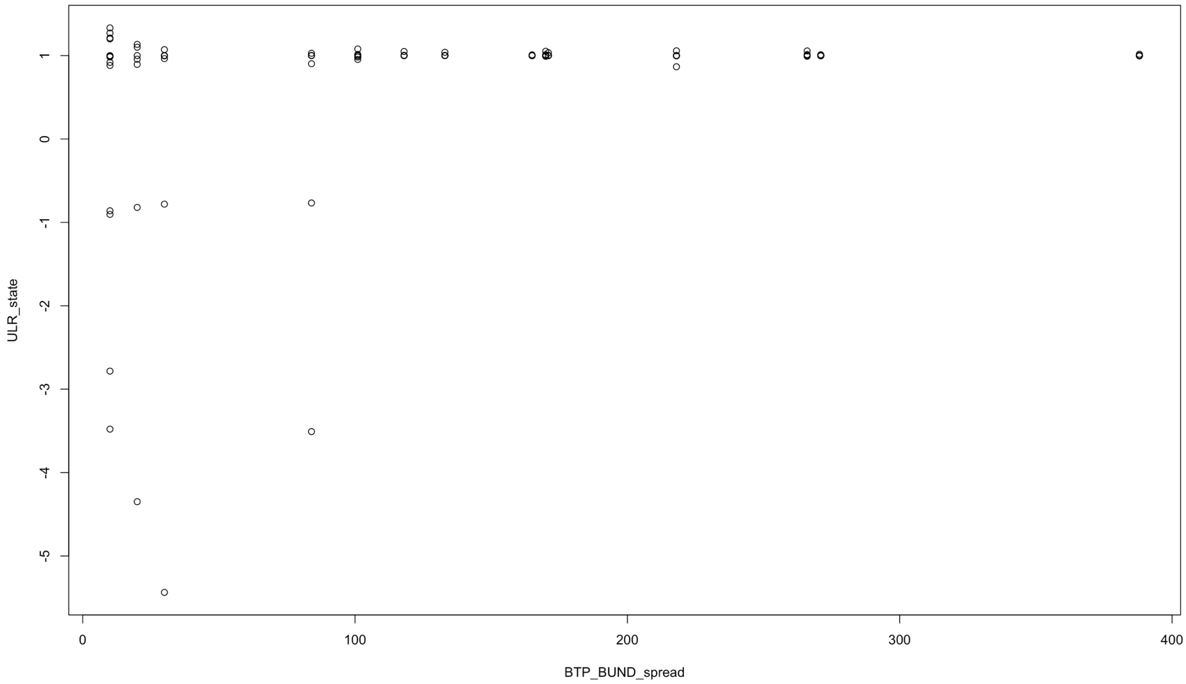
The baseline specification is therefore given by:

$$ULR_{ijt} = \alpha_i + \beta_1 LEV_{it} + \beta_2 ROA_{it} + \beta_3 TIER1_{it} + \beta_4 SIZE_{it} + \varepsilon_{ijt}$$

For the specification of the Uninsured Loan Ratio that refers to the government bonds, we can include in the regression a measure of the riskiness of this type of exposure. In particular, we use as a proxy of the state riskiness, the BTP–BUND spread calculated year–by–year as the average of the monthly basis point spread reported and downloaded from the website "investing.com".

However, we cannot find data before year 2007 thus we assume that for the three years from 2007 to 2004, it remains at a low level between 20 and 10 basis point. This assumption is supported by the awareness that in that period the infamous spread was almost unknown to the majority, only the expertise in the sector were aware of the instrument.

The following plot represents the relationship between the BTP–BUND spread and the uninsured loans ratio of sovereign.



Plot 3.1: Scatterplot of uninsured loans ratio of the state and BTP—BUND spread.

The same implementation cannot be extended to the other two specifications because we would need the CDS spread of all the single reference entity but given the assumption that we made we are not able to retrieve such information. We take the value of the loans to corporate and other banks as a whole since we do not have deeply and specify information about which corporate or banks are there behind those loans. Consequently, we consider exposure to corporate as a unique reference entity.

Thus, when we talk about government bonds, therefore when the reference entity is the sovereign, the specification becomes:

$$ULR_{ijt} = \alpha_i + \beta_1 LEV_{it} + \beta_2 ROA_{it} + \beta_3 TIER1_{it} + \beta_4 SIZE_{it} + \beta_5 BTP\_BUNDspread_t + \varepsilon_{ijt}$$

In this way, we control also for time–varying riskiness of the instrument.

Specifically, LEV_{it} captures the leverage of the bank i in the year t, which is calculated as the end–year total assets divided by the contemporaneous value of equity; ROA_{it} gives information about the bank i in the year t performance and it's the ratio between net profit or loss and total assets; moreover, $TIER1_{it}$ captures bank's financial strength, it is the regulatory capital ratio computed as equity capital and disclosed reserves over its total risk–weighted assets. It is a key measure that has been adopted as part of the Basel III Accord on bank regulation.

$SIZE_{it}$, gives an idea of the dimension of the several banks and is the result of the natural logarithm of the year–end total assets. These are in brief described the main explanatory variables that we use in running our regression model.

However, all the details of the regression (i.e. the R code) are presented in the Appendix A.

Under Hypothesis 1, we expect β_3 to be positive, i.e. lower regulatory capital values should be associated with a larger share of the credit exposure being insured. Based on Hypothesis 2, we expect the coefficients to be positive when looking at bank risk measure so to the leverage parameter ($\beta_1 > 0$) and negative when considering the bank's profitability $\beta_2 < 0$, thus to the return on assets.

Here is presented the head of the data we create to implement the analysis, in particular Table 3.3 shows the Banca Nazionale del Lavoro (BNL) example sorted for the period from 2004 to 2017 (which, actually, continue up the year 2018), with all its explanatory and dependent variables for the several specifications.

	bank	year	alfa_i	ULR_state	ULR_banks	ULR_corporate	LEV	ROA	TIER1	SIZE	BTP_BUND_spread
Bnl–2004	Bnl	2004	3	1.2700012	0.8874209	0.7649230	20.776535	−0.0433426038	8.320000	12.84761	10
Bnl–2005	Bnl	2005	3	1.1998122	0.9243968	0.8368960	19.977437	−0.0416755806	8.000000	12.35347	10
Bnl–2006	Bnl	2006	3	1.1335023	0.9629133	0.9156412	19.209074	−0.0400726736	7.650000	11.87833	20
Bnl–2007	Bnl	2007	3	1.0708571	1.0030347	1.0017956	18.470264	−0.0385314170	7.400000	11.42147	30
Bnl–2008	Bnl	2008	3	1.0278655	1.0033694	1.0018453	18.043107	0.1565959876	7.000000	11.40507	84
Bnl–2009	Bnl	2009	3	1.0129161	1.0016589	1.0010263	18.601999	0.2394190000	9.900000	11.46085	101
Bnl–2010	Bnl	2010	3	1.0102270	1.0048377	1.0008902	19.209547	0.0064540000	10.100000	11.43987	170
Bnl–2011	Bnl	2011	3	1.0109413	1.0053787	1.0008851	18.311089	0.2227602900	7.700000	11.44352	266
Bnl–2012	Bnl	2012	3	1.0000000	1.0000000	1.0000000	15.195676	0.0620143700	8.500000	11.31738	388
Bnl–2013	Bnl	2013	3	1.0000000	1.0000000	1.0000000	13.636807	0.1165450000	8.400000	11.23198	271
Bnl–2014	Bnl	2014	3	1.0000000	1.0000000	1.0000000	13.560821	−0.1686905000	9.700000	11.22114	165
Bnl–2015	Bnl	2015	3	1.0000000	1.0000000	1.0000000	13.718180	0.0219371822	11.400000	11.25796	118
Bnl–2016	Bnl	2016	3	1.0000000	1.0000000	1.0000000	14.090909	0.1581276700	12.000000	11.27780	133
Bnl–2017	Bnl	2017	3	1.0000000	1.0000000	1.0000000	13.627935	0.1887676000	9.125000	11.27635	171

Table 3.3: Example of dataset used.

3.5 Results

Having in mind the main assumptions, hypothesis and how results should look like in order to consider Credit Default Swap either hedging or a capital relief instrument, we have a look at the main outcomes.

3.5.1 Descriptive statistics

Our sample contains 8 Italian banks lending to several different firms and banks, we obtain fourteen years data from 2004 to 2018.

All 8 banks are active on CDS's market in the sense that the bank should have, at least for one time bought or sold a Credit Default Swap. Banks are also an active provider of loans and contributor in financing the Italian public debt.

3.5.2 Dependent variables

ULR_state	ULR_banks	ULR_corporate
Min. :-5.4362	Min. :0.3131	Min. :0.7107
1st Qu.: 0.9959	1st Qu.:0.9844	1st Qu.:0.9928
Median : 0.9999	Median :0.9998	Median :0.9999
Mean : 0.6888	Mean :1.0232	Mean :1.0152
3rd Qu.: 1.0006	3rd Qu.:1.0011	3rd Qu.:1.0010
Max. : 1.3319	Max. :2.6951	Max. :1.8346
NA's :15		

Table 3.4: Summary statistics for dependent variables.

For banks exposures against sovereign, we observe an average share of Uninsured Loans Ratio (ULR) of 68.88%, the lowest between the three specifications. Moreover, is the only case where, on average, banks have a ULR lower than one which means that Italian banks partially hedge the exposures they have over the government.

On the contrary, in the other two cases, banks seem to double their credit exposures since the Uninsured Loans Ratios are on average a little more than 1 (or equivalently a little more than a 100%; i.e. 102.32% and 101.52% respectively).

Actually, following this evidence and given the hedging hypothesis, it would seem that our financial intermediaries are more confident about corporates and other banks reliability, rather than the Italian government solvency in repaying its debt obligations; which appears a quite realistic result.

However, the lowest value of ULR is reached by Monte dei Paschi di Siena in 2007 in lending money to the Italian government; while the highest value occurred in 2008 when Mediobanca gave loans to other banks, which clearly demonstrate that this bank, at that time, felt other bank's soundness and robustness.

Notice here that ULR_state variable, in Figure 3.3, presents 15 NAs which are all accounted to Mediobanca because we do not find any acquisition of government bonds in the bank balance sheet, that in turn make the Uninsured Loans Ratio incalculable.

3.5.3 Explanatory variables

LEV	ROA	TIER1	SIZE	BTP_BUND_spread
Min. : 7.432	Min. :-3.0008115	Min. : 4.739	Min. :10.79	Min. : 10.0
1st Qu.:11.884	1st Qu.: 0.0006115	1st Qu.: 7.647	1st Qu.:11.28	1st Qu.: 30.0
Median :13.647	Median : 0.1968111	Median : 9.765	Median :11.81	Median :133.0
Mean :14.345	Mean : 0.1554729	Mean : 9.878	Mean :12.18	Mean :143.7
3rd Qu.:15.381	3rd Qu.: 0.5290909	3rd Qu.:12.080	3rd Qu.:13.08	3rd Qu.:218.0
Max. :34.634	Max. : 1.8710286	Max. :15.360	Max. :16.02	Max. :388.0

Table 3.4: Summary statistics for explanatory variables.

Leverage is defined as the ratio between total year–end bank assets over the contemporaneous equity and its average level in our sample is about 14.3. The bank that shows the highest leverage (i.e. 34.6) is Monte dei Paschi di Siena in year 2012 and the lower is Mediobanca in 2007.

The average balance sheet size of banks in our sample amounts to (in logs) 12.18, with the largest bank in our sample being UniCredit and the bank with the smallest amounts of total assets being BPER Banca.

Moreover, the minimum of the BTP–BUND spread is reached in the years were first came to our attention, thus in years 2004–2005 then started growing up, picking its maximum in year 2012 (we remember that this measure is the result of an average of the monthly basis point which is an average itself; thus it maybe that there were historically higher or lower values than the ones reported but given the calculation of the variable by means of the arithmetic mean, those extreme values are averaged out).

Finally, concerning the profitability, banks in our sample have on average positive return on total assets but again Monte dei Paschi di Siena in year 2014 picked the minimum of minus 3.001; whereas looking to the regulatory capital we find an average of 9.878% of Tier 1 ratio which is tiny higher than the mandatory requirements but in several circumstances the requirement was not satisfied, indeed the minimum is 4.7%.

3.6 Working environment

The entire project implementation has been performed in the Software RStudio. We attempt a panel regression analysis and carry out a series of Fixed effects (i.e. Within Group and Between Effect) and Random Effects panel regressions of the model above presented.

In the Appendix A, as yet specified, there are all the details of the R code used to perform the empirical analysis.

3.7 Main regression outcomes

We now provide regression outcomes for the two hypotheses outlined. We absorb all time constant bank factors by including bank fixed effects as well as all factors that are constant for all loans by including time fixed effects.

In a Random Effects Model, we do not assume that the effects of the time invariant variables, such as bank and counterparty, are the same and allow them to have their own starting values (i.e. intercepts). In this model, the R code is almost identical, except that in the model section we change Within to Random.

The WG (within group) estimator requires strict exogeneity of the explanatory variables with the respect to the error term but allows for correlation between the explanatory variables and the individual effect.

The Within Group estimator takes deviations from group means (individual) for all variables. The two estimators, Random and Within, require weaker conditions to be considered consistent with the respect to the Random Effect.

Indeed, for the Within Group the needed conditions are:

- Strict exogeneity, i.e. $\mathbb{E}[\varepsilon_{it}|X_{is}] = 0;\ \forall t, s$ where the X's are the explanatory variables and s identifies a time–period $s \leq t$.
- Moreover, the individual effect in the model may correlates with the explanatory variables.

For the Random Effect the conditions to be met are the following:

- Strict exogeneity, i.e. $\mathbb{E}[\varepsilon_{it}|X_{is}] = 0;\ \forall t, s$.
- The individual effect in the model cannot correlates with the explanatory variables differently from before.

Then we get the value of the parameter estimate, which is the average change in ULR over time between banks.

⇒ <u>*Hypothesis 1: Hedging/speculating behavior.*</u> Results for our first hypothesis and specification, i.e. Credit Default Swap as protection against government bonds riskiness, are now presented.

Essentially, the concept is that healthier banks tend to insure larger shares of their loan exposures. First, the script in Figure 3.2 shows the outcomes of the Within Model regression.

```
Oneway (individual) effect Within Model

Call:
plm(formula = ULR_state ~ alfa_i + lag(BTP_BUND_spread, 1) +
    lag(LEV, 1) + lag(ROA, 1) + lag(TIER1, 1) + lag(SIZE, 1),
    data = empirical_model, model = "within")

Balanced Panel: n = 7, T = 14, N = 98

Residuals:
     Min.   1st Qu.    Median    3rd Qu.      Max.
-3.969441 -0.195062  0.038936  0.355884  2.139326

Coefficients:
                          Estimate Std. Error t-value Pr(>|t|)
lag(BTP_BUND_spread, 1)  0.0010193  0.0010445  0.9759 0.331847
lag(LEV, 1)              0.0168084  0.0318392  0.5279 0.598917
lag(ROA, 1)             -0.5324584  0.1593255 -3.3420 0.001233 **
lag(TIER1, 1)            0.0218661  0.0389059  0.5620 0.575560
lag(SIZE, 1)             0.1412088  0.1931907  0.7309 0.466809
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    89.898
Residual Sum of Squares: 65.964
R-Squared:      0.26624
Adj. R-Squared: 0.17238
F-statistic: 6.24083 on 5 and 86 DF, p-value: 5.5222e-05
```

Figure 3.2: Results of Within Model regression for sovereign exposures.

Among all the coefficients, we find only the negative estimate of ROA as a statistically significant coefficient, in particular it is significant at 0.1% level, which indicates that more profitable banks insure more often their loans than less profitable banks.

Note, furthermore, that each independent variable is lagged by one period. For the regressions on the second and third model (Random Effect and Between Models, respectively in Figure 3.3 and 3.4), some sign reverses compared to our first regression.

The coefficient ROA remains negative in the Random Effect but turns positive in the Between Model contradicting our first result, but this time is not statistically significant. In addition, in the Between Model leverage and Tier 1 ratio estimates become negative. No one throughout all the coefficients results statistically significant despite, within the three used for this type of exposures, it is the model with the highest R squared indicator.

```
Oneway (individual) effect Random Effect Model
   (Swamy-Arora's transformation)

Call:
plm(formula = ULR_state ~ alfa_i + lag(BTP_BUND_spread, 1) +
    lag(LEV, 1) + lag(ROA, 1) + lag(TIER1, 1) + lag(SIZE, 1),
    data = empirical_model, model = "random")

Balanced Panel: n = 7, T = 14, N = 98

Effects:
                 var std.dev share
idiosyncratic 0.7670  0.8758  0.65
individual    0.4132  0.6428  0.35
theta: 0.6579

Residuals:
    Min.  1st Qu.   Median  3rd Qu.     Max.
-4.44063 -0.16397  0.12610  0.36879  1.67758

Coefficients:
                          Estimate Std. Error z-value Pr(>|z|)
(Intercept)             -1.6129869  2.1102472 -0.7644 0.444653
alfa_i                   0.1046018  0.1117261  0.9362 0.349152
lag(BTP_BUND_spread, 1)  0.0010834  0.0010391  1.0426 0.297113
lag(LEV, 1)              0.0080773  0.0307461  0.2627 0.792774
lag(ROA, 1)             -0.5027384  0.1582868 -3.1761 0.001493 **
lag(TIER1, 1)            0.0255324  0.0390531  0.6538 0.513249
lag(SIZE, 1)             0.1127099  0.1643052  0.6860 0.492726
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    92.953
Residual Sum of Squares: 70.559
R-Squared:      0.24092
Adj. R-Squared: 0.19087
Chisq: 28.8819 on 6 DF, p-value: 6.4049e-05
```

Figure 3.3: Results of Random Effect Model for sovereign exposures.

Generally, these outcomes are in line with our original expectation, except for the fact that in our first definition of weaker bank we assumed the banks are “weak” if they score relatively poorly on risk (highly leveraged banks) and profitability (low return on assets), thus one condition is met (i.e. the results on the estimate of the return on assets) the other not.

Since we assumed that all banks in our sample have a lending exposures toward the three macro–category of counterparties that we created, we cannot follow the analysis made by Minton *et al.* (2008) that namely make a distinction between banks with and without a lending exposure to test the hedging hypothesis; for this reasons we think that this ambiguous result, in reality, is quite a common phenomenon. In this way we mean that the leverage is yet a fundamental indicator since banks need, always, to be well capitalised to tackle any crisis situation, but it doesn't tell, at any time, which is the actual riskiness level of the bank/firm.

Leverage ratio may be misleading sometimes given the fact that a firm or a bank can have a high level of indebtedness, but it may be investing in a good project that have a positive return only in the future.

At the moment of the evaluation the bank results risky but in reality if it is a good investment, it'll turn out as a profitable one.

Leverage coefficient is sometimes positive whereas it should be positive in order to support our hypothesis but, however it is never statically significant in this first specification, so we are quite confident in asserting that weaker banks insure little of the exposures in government bonds using Credit Default Swaps.

```
Oneway (individual) effect Between Model

Call:
plm(formula = ULR_state ~ alfa_i + lag(BTP_BUND_spread, 1) +
    lag(LEV, 1) + lag(ROA, 1) + lag(TIER1, 1) + lag(SIZE, 1),
    data = empirical_model, model = "between")

Balanced Panel: n = 7, T = 14, N = 98
Observations used in estimation: 7

Residuals:
      Bnl      Bper       Bpm    Intesa       Mps       Ubi Unicredit
 0.441052 -0.308944  0.158347 -0.106462 -0.354273  0.056557  0.113724

Coefficients:
                Estimate Std. Error t-value Pr(>|t|)
(Intercept)    6.8329340 13.3441451  0.5121   0.6987
alfa_i         0.0056155  0.1264791  0.0444   0.9718
lag(LEV, 1)   -0.1625842  0.2588858 -0.6280   0.6430
lag(ROA, 1)    0.7366732  1.1752221  0.6268   0.6435
lag(TIER1, 1) -0.4752470  1.5970336 -0.2976   0.8159
lag(SIZE, 1)   0.0601810  0.5461490  0.1102   0.9301

Total Sum of Squares:    1.8639
Residual Sum of Squares: 0.46802
R-Squared:      0.74891
Adj. R-Squared: -0.50656
F-statistic: 0.596515 on 5 and 1 DF, p-value: 0.74803
```

Figure 3.4: Results of Between Model for sovereign exposures.

However, in the following figures are presented all together the three models for the remaining two specifications (exposures against other banks and corporates). Figure 3.5 refers to the loans to other banks instead Figure 3.6 to loans to corporates. If we focus our attention on the results in Figure 3.5 we can notice that now the ROA estimates among the different methods is no longer negative, even the leverage estimate turns out only in one case negative but is not significant. Then in situation where the reference entities are other banks, we do not find support for the hedging hypothesis.

Within Model

```
Coefficients:
                 Estimate Std. Error t-value Pr(>|t|)
lag(LEV, 1)    0.00076695 0.00946756  0.0810 0.935598
lag(ROA, 1)    0.03056561 0.04407316  0.6935 0.489591
lag(TIER1, 1)  0.03082342 0.01056383  2.9178 0.004353 **
lag(SIZE, 1)   0.07593136 0.05403128  1.4053 0.163025
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    7.7824
Residual Sum of Squares: 7.032
R-Squared:      0.096427
Adj. R-Squared: -0.0029663
F-statistic: 2.66793 on 4 and 100 DF, p-value: 0.036576
```

Random Model

```
Coefficients:
                 Estimate Std. Error z-value  Pr(>|z|)
(Intercept)     0.9792178  0.3704486  2.6433   0.00821 **
alfa_i          0.0051020  0.0126906  0.4020   0.68766
lag(LEV, 1)    -0.0017244  0.0080851 -0.2133   0.83110
lag(ROA, 1)     0.0955474  0.0401864  2.3776   0.01743 *
lag(TIER1, 1)   0.0430975  0.0102054  4.2230 2.411e-05 ***
lag(SIZE, 1)   -0.0321643  0.0282005 -1.1406   0.25405
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    10.62
Residual Sum of Squares: 8.2056
R-Squared:      0.22735
Adj. R-Squared: 0.1909
Chisq: 31.19 on 5 DF, p-value: 8.5919e-06
```

Between Model

```
Coefficients:
                 Estimate Std. Error t-value Pr(>|t|)
(Intercept)     0.5369886  0.5022881  1.0691  0.36341
lag(LEV, 1)     0.0079558  0.0124215  0.6405  0.56742
lag(ROA, 1)     0.1104536  0.0945023  1.1688  0.32691
lag(TIER1, 1)   0.1208522  0.0417635  2.8937  0.06282 .
lag(SIZE, 1)   -0.0672713  0.0241250 -2.7885  0.06851 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    0.20269
Residual Sum of Squares: 0.0091672
R-Squared:      0.95477
Adj. R-Squared: 0.89447
F-statistic: 15.8327 on 4 and 3 DF, p-value: 0.023394
```

Figure 3.5: Results of Within Effect, Random Effect and Between Model for other banks exposures.

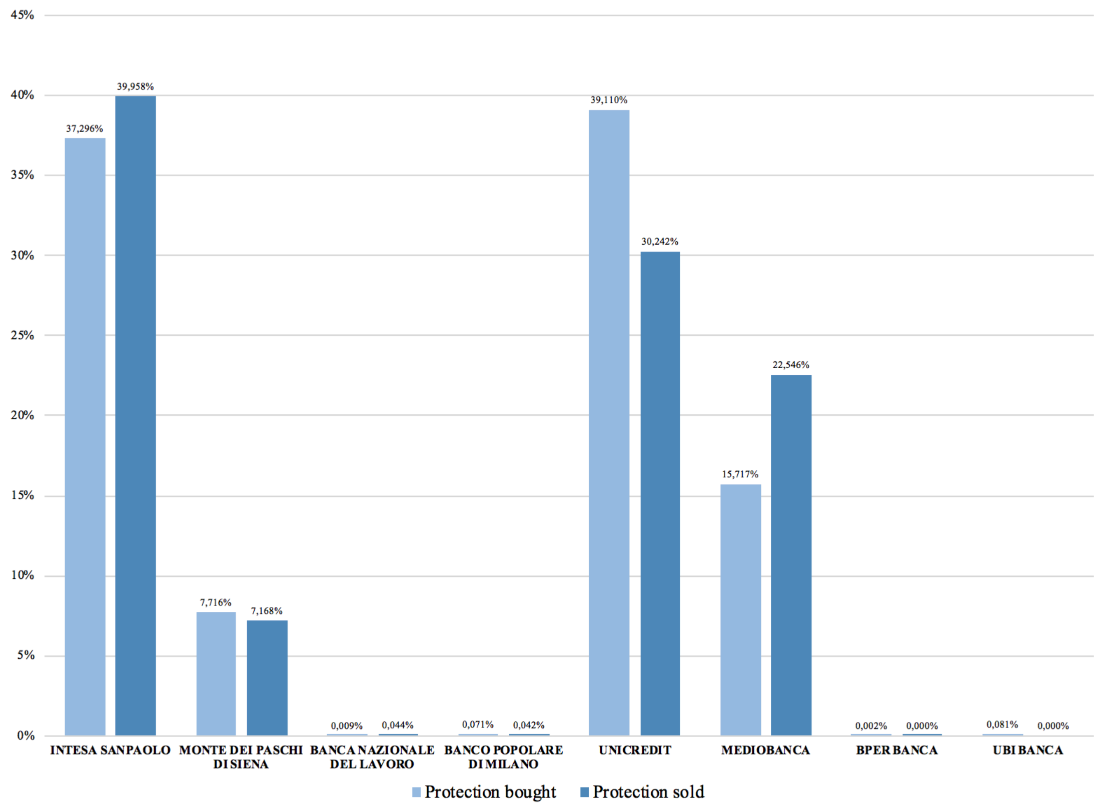
Thus, under this specification, the lender bank may not use Credit Default Swap as a hedging instrument given the same explanation proposed in the protection of exposures toward government bonds, or generally speaking, the state. These results are in contrast to those of Aldasoro *et al.* (2017), who use an analogous empirical design but a very different data set. They focus on a cross–country sample, they use different sample specification. The broadest includes 1˙022 European banks from 28 countries, whereas the narrowest is composed by 142 banks with very different business models.

To the contrary we focus only on 8 major banks. Indeed, we want to specify that concentrate our attention only on the Italian case, has its pro and cons since, certainty we made our own analysis that directly involves our daily life; but on the other side, it may be a limitation since by studying each bank's balance sheet we notice that is not as common as instrument in Italy.

However, the following graph represents the composition of the net CDS position, in particular it shows which are the major banks among the ones analyzed, that act in the Credit Default Swaps market.

It is quite evident from Graphic 3.1 that the most influential actors are Intesa Sanpaolo and UniCredit, which together represent almost 80% of the total amount of CDS considered by us either bought or sold.

Mediobanca, also has its good market's fraction, indeed considering the three majors all together we reach the 90/95% of the total.



Graphic 3.1: Composition of Italian Credit Default Swaps protection bought and sold.

This is a very crucial element in our analysis. Our research question focuses on establishing whether or not banks use CDS as capital relief and/or hedging instrument; but in order to have a complete framework of the situation we have to consider which is the worldwide relevance of what we find.

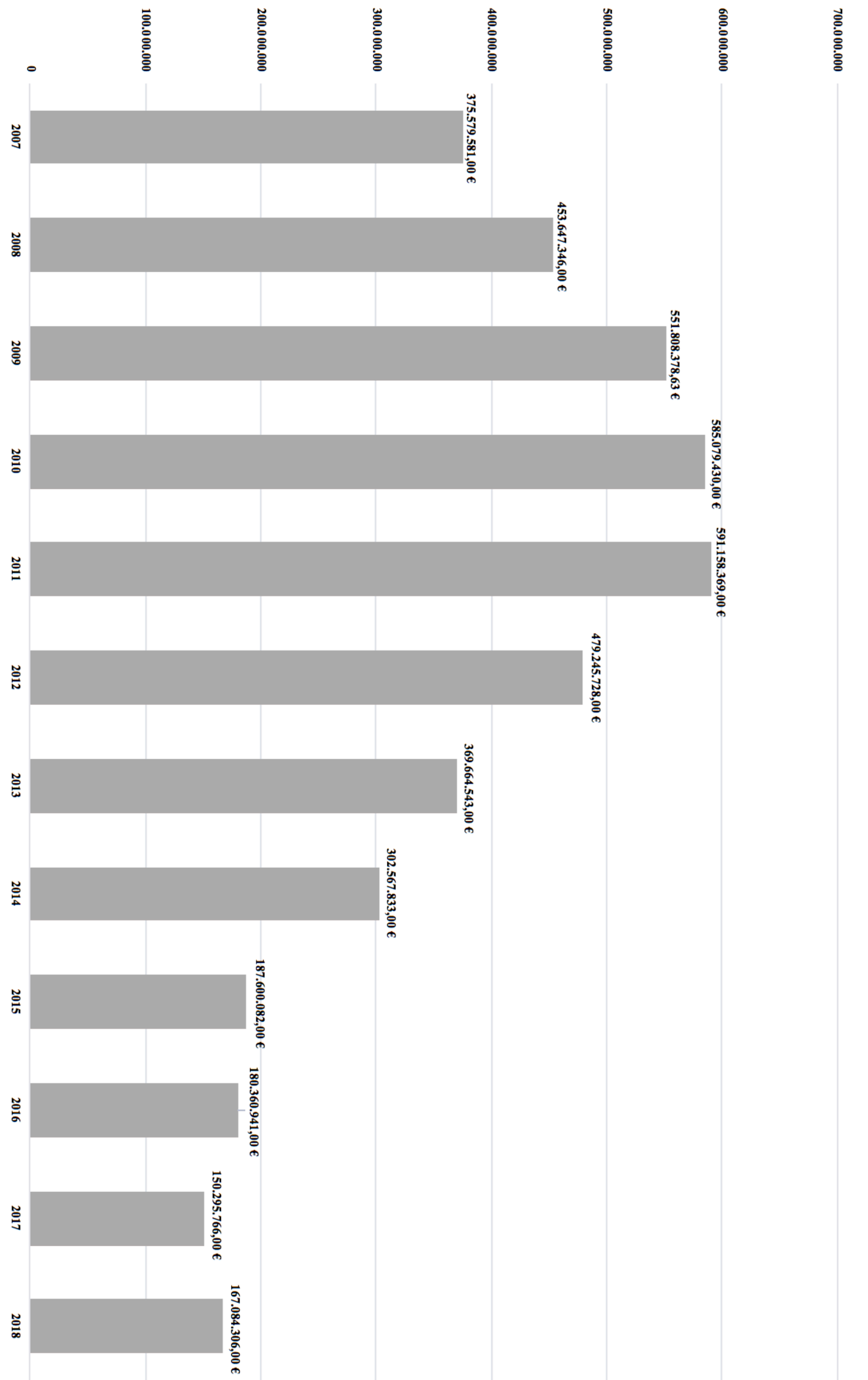
Generally speaking, the same author of the paper from which we inspired our work has published on BIS website the quarterly review in June 2018 and its abstract reports the following sentences "*Over the last decade, the size and structure of the global Credit Default Swap (CDS) market have changed markedly. With the help of the BIS derivatives statistics, we document how outstanding amounts have fallen, central clearing has risen, and the composition of underlying credit risk exposures has evolved. Netting of CDS contracts has increased, due to the combination of a higher share of standardized index products and the clearing of such contracts via central counterparties. In turn, this has led to a further reduction in counterparty risk.*

Underlying credit risks have shifted towards sovereigns and portfolios of reference securities with better credit ratings. The distribution of credit risks across counterparty categories has remained broadly unchanged."[18]

Which outline the most recent changes in the Credit Default Swap market. With the data and the scenario just described in mind, we now look at Italy which has a peculiar pattern represented in the following Figure (amounts are in thousand €).

From 2007 to 2011 CDS notional amounts of the eight Italian banks rapidly increased but then suddenly started its decline up 2017 and only in the last year it had a little recovery.

[18] Cit. from https://www.bis.org/publ/qtrpdf/r_qt1806b.pdf – Aldasoro I. and Ehlers T., (2018).



Graphic 3.2: Italian CDS pattern from 2007 to 2018.

Specifically, our Italian total notional amount in 2018 sum up to 167˙084˙306˙000.0€ that represents around 2.6% since as Table 1.1 in the previous Section shows, the global notional amount in the second semester of year 2018 was 8˙143$ billion, which converted at 31 December 2018 exchange ratio it corresponds to 7˙092˙553˙000˙000.0€. Thus, these are the numbers and relevance of what we are talking about.

However, as shown in Figure 3.6 we obtain a positive and highly statistically significant coefficient for the bank's regulatory capital which is related to the second hypothesis of capital relief. It is extremely significant in the random model and statistically significant at 0.1% and 5% levels in the other two regression models. Lastly, in the third specification we find a different scenario, where this time the coefficient of bank's leverage remains always negative, as to ascertain the hedging strategy in using the Credit Default Swaps to insure exposure to firms but the return on assets coefficient is, on the contrary, always negative thus we don't know which of the two estimates predominate.
For these reasons we are not able to assert which is the actual use of this instrument, whether to hedge exposures or not.

Within Model

```
Coefficients:
                Estimate Std. Error t-value Pr(>|t|)
lag(LEV, 1)   -0.0012087  0.0049590 -0.2437 0.807928
lag(ROA, 1)    0.0060541  0.0230849  0.2623 0.793664
lag(TIER1, 1)  0.0148265  0.0055332  2.6796 0.008621 **
lag(SIZE, 1)   0.0524138  0.0283008  1.8520 0.066973 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    2.1363
Residual Sum of Squares: 1.9292
R-Squared:      0.096909
Adj. R-Squared: -0.0024312
F-statistic: 2.6827 on 4 and 100 DF, p-value: 0.03576
```

Random Model

```
Coefficients:
                Estimate Std. Error z-value  Pr(>|z|)
(Intercept)    0.9070155  0.1894288  4.7882 1.683e-06 ***
alfa_i         0.0096531  0.0064893  1.4875 0.1368728
lag(LEV, 1)   -0.0019642  0.0041343 -0.4751 0.6347145
lag(ROA, 1)    0.0310851  0.0205493  1.5127 0.1303541
lag(TIER1, 1)  0.0188902  0.0052185  3.6198 0.0002948 ***
lag(SIZE, 1)  -0.0080783  0.0144203 -0.5602 0.5753435
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    2.6791
Residual Sum of Squares: 2.1456
R-Squared:      0.19912
Adj. R-Squared: 0.16134
Chisq: 26.3547 on 5 DF, p-value: 7.6156e-05
```

Between Model

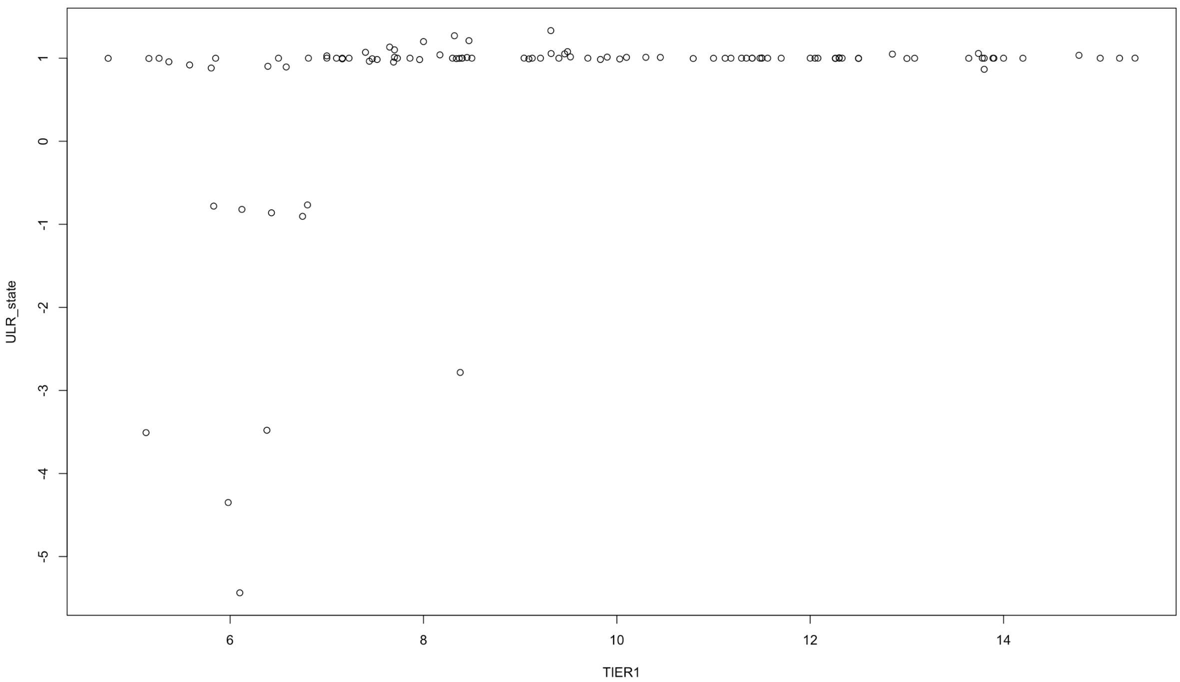
```
Coefficients:
                Estimate Std. Error t-value Pr(>|t|)
(Intercept)    0.8969277  0.0705495 12.7134  0.00613 **
alfa_i         0.0036616  0.0013341  2.7446  0.11107
lag(LEV, 1)   -0.0026778  0.0017178 -1.5588  0.25938
lag(ROA, 1)    0.0066356  0.0123742  0.5362  0.64545
lag(TIER1, 1)  0.0488270  0.0054642  8.9358  0.01229 *
lag(SIZE, 1)  -0.0276627  0.0032319 -8.5592  0.01338 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    0.03877
Residual Sum of Squares: 0.00010429
R-Squared:      0.99731
Adj. R-Squared: 0.99059
F-statistic: 148.301 on 5 and 2 DF, p-value: 0.0067113
```

Figure 3.6: Results of Within Effect, Random Effect and Between Model for corporate exposures.

⇒ <u>*Hypothesis 2: Capital relief.*</u> Remembering that the bank capital accord (i.e. Basel accords) allows banks to apply a lower risk weight to the claims they hold if they use credit risk mitigants such as credit derivatives to hedge the credit risk exposure from a higher–rated counterparty. Or, put differently, credit derivatives allow banks to "rent" another institution's credit rating to reduce its required capital[19].

Thus, now coming back to the previous figures we have a look at what is about the second hypothesis. As can also be seen in Figure 3.2, 3.3 and 3.4, we find support for the capital relief hypothesis in the first scenario where banks are exposed toward government bonds, expect in the between model although in that case the estimate is not statically significant.

Plot 3.2 presents the relationship between Tier 1 ratio and the Uninsured Loans Ratio for the scenario just specified.



Plot 3.2: Scatterplot of Uninsured Loans Ratio of the state and Tier 1 ratio.

[19] http://www.cftc.gov/PressRoom/SpeechesTestimony/opagensler-32

Under the latter, one would expect to see banks with lower regulatory capital ratios having higher incentives to use the Credit Default Swaps market in order to hedge their credit risk exposures, thereby obtaining capital relief via a sort of risk–weighting arbitrage.
In the context of our empirical setting, this should translate into a positive coefficient for the Tier 1 ratio: higher regulatory capital ratios should be associated with a higher share of the loan being uninsured, thus higher ULR.

Overall, these results, together with the ones obtained in the other two specification (protection toward other banks and corporates), are in line with our expectation, supporting our second hypothesis of capital relief strategy. Indeed, throughout all the specification, Tier 1 ratio coefficient seems to remain always positive and statistically significant in the two scenarios of exposures of banks toward other banks and corporates.
Results are often highly statistically significant such as in the case of the two Random Effect regression model (one for CDS versus other banks and the other versus corporates), where the significance level are at 0%.
In conclusion, one may argue that Italian banks use CDS to comply with the regulatory requirements and deceive regulators which become less effective than perceived.

However, we also run the Hausman test, which is a statistical hypothesis test, to evaluate the consistency of the estimator when compared to an alternative, less efficient estimator which is already known to be consistent.

The Within Group (WG) estimator is consistent under weaker conditions than the Random Effect estimator, as specified above.

However, the Random Effect estimator, when consistent, is more efficient than the WG estimator. The Random Effect estimator combines between groups variability with within–group variability. Instead, the Within Group estimator, as its name suggests, uses only within–group variability.

Hence, to decide which estimator one should use, we can compute the Hausman test. We run the test for every regression we made, and we find out from the Hausman test for Within Model versus Random Effects Model the following p–values presented in Figure 3.7. Under the null hypothesis H_o: Random Effect model is a better fit although even the Within Group is consistent, but it is inefficient; whereas under the alternative H_1: Within Effect model is a better fit since the Random Effect estimator is, in that case, inconsistent.

```
> # Hausman test for fixed versus random effects model state
> phtest(RE_state,FE_state)

	Hausman Test

data:  ULR_state ~ alfa_i + lag(BTP_BUND_spread, 1) + lag(LEV, 1) +  ...
chisq = 6.8704, df = 5, p-value = 0.2305
alternative hypothesis: one model is inconsistent

>
> # Hausman test for fixed versus random effects model banks
> phtest(RE_banks,FE_banks)

	Hausman Test

data:  ULR_banks ~ alfa_i + lag(LEV, 1) + lag(ROA, 1) + lag(TIER1, 1) +  ...
chisq = 15.546, df = 4, p-value = 0.003693
alternative hypothesis: one model is inconsistent

>
> # Hausman test for fixed versus random effects model corporate
> phtest(RE_corporate,FE_corporate)

	Hausman Test

data:  ULR_corporate ~ alfa_i + lag(LEV, 1) + lag(ROA, 1) + lag(TIER1,  ...
chisq = 9.8313, df = 4, p-value = 0.04337
alternative hypothesis: one model is inconsistent
```

Figure 3.7: Hausman test for Within Effect versus Random Effect Model.

In the first scenario, where counterparty is sovereign the p–value is above 0.05 which means that Random Effect better summarizes the model rather than the Within Effect. In that case we accept the null hypothesis.

To the contrary, in the other scenarios the results overturn and Random Effect become the worst available fit for the model analyzed, since turns out to be inconsistent and we refuse the null hypothesis.

Now, moving toward the comparison between, again, the Random Effect model and the Between Effect we find out the same evidence. Indeed, for sovereign exposure, Random Effect seems fit better instead for corporate and other banks exposures, the alternative, that in this case is the Between Effect appears to be suitable for the analysis.

```
> # Hausman test for between versus random effects model state
> phtest(RE_state,BW_state)

        Hausman Test

data:  ULR_state ~ alfa_i + lag(BTP_BUND_spread, 1) + lag(LEV, 1) +  ...
chisq = 4.9935, df = 5, p-value = 0.4167
alternative hypothesis: one model is inconsistent

>
> # Hausman test for between versus random effects model banks
> phtest(RE_banks,BW_banks)

        Hausman Test

data:  ULR_banks ~ alfa_i + lag(LEV, 1) + lag(ROA, 1) + lag(TIER1, 1) +  ...
chisq = 71.166, df = 4, p-value = 1.288e-14
alternative hypothesis: one model is inconsistent

>
> # Hausman test for between versus random effects model corporate
> phtest(RE_corporate,BW_corporate)

        Hausman Test

data:  ULR_corporate ~ alfa_i + lag(LEV, 1) + lag(ROA, 1) + lag(TIER1,  ...
chisq = 51.718, df = 5, p-value = 6.164e-10
alternative hypothesis: one model is inconsistent
```

Figure 3.8: Hausman test for Random Effect Model versus Between Effect.

Conclusions

Credit Default Swap is a recent financial innovation that has played a key role in the financial markets, especially in the subprime crisis phase.

Opinions on that instrument are very contrasting, for some CDS represents a useful instrument that helps the users to keep under control the credit exposures and risks, for others it determines, a mean of pure speculation and a deterrent to avoid maintaining amount of reserves of capital as the Basel III requires.

In this dissertation, starting from reviewing the Credit Default Swap contribution in the financial world, deepening the analysis by going through its relationship with banks, we want to perform our empirical work in the domestic context.

We combine loans data from a group of bank's balance sheets for each year, from 2004 to 2018, with the notional amount of CDS bought and sold to the reference entity toward which the bank is exposed to; we use these data to construct a measure that represent the part of the loan not insured with a Credit Default Swap and then with this variable (i.e. our dependent variable) we run a Fixed Effect and Random Effect model regression. With this panel setting we aim to shed light on how banks use the CDS protection contract.

We first investigate the relationship between bank's health and the hedging behavior, in that case we proxy the soundness/health of the bank by looking into two main measures that are: the leverage ratio and the return on assets. Both indicators give us an idea of how bank is performing, therefore controlling for these variables we find not unique evidence on the hedging hypothesis.

In particular, we segment the exposures into three macro–areas, the first concern about exposures toward government, the second toward other banks and the last one exposure versus corporates. In all the three specification, for what concern the hedging hypothesis we do not find clear evidence of this type of bank's behavior.

On the contrary, but in line with the previous literature (Hasan and Wu, 2016) we find support to the capital relief hypothesis, indeed we test whether or not the strategy of using credit derivatives to “rent” another counterparty's credit rating, thus, to reduce bank' required capital, is exploited also from our eight Italian's banks.

Moreover, having in mind the structure of how we implement our dataset, we want to highlight some aspects to take into consideration in future works, such as extend the analysis to an European sample may increase the accuracy of the results, test other hypothesis in order not to limit the possible explanation to give to some banks' behavior or, more, try to have access to platforms with deeper information about exposures and CDS–bank relationship in order to avoid making strong assumptions.

However, if we focus on the results obtained in the empirical section, we are able to comments which may be the possible implication for our policy maker, banks and markets. Indeed, the evidence that there is support for the capital relief hypothesis, suggests negative implication for the policy maker and regulators which theoretically, have the objective to make things mandatory but, in reality, what happen is that banks bypass this regulation, in particular the one concerning the capital requirement. Banks, on the other hand, have less constraint in term of liquidity available, because they can use more capital than in the situation in which they cannot exploit the capital relief but, at the same time, they are paying continuously the premium.

This condition may lead to an increase of the Credit Default Swap contract in circulation in the markets, the larger is the use the banks make to carry on this strategy.

Appendix A

R Code

```
# Load data
library(readxl)
one_model <- read_excel("Desktop/one_model.xlsx")


# Adjust data
library(plm)
one_model$BTP_BUND_spread<-as.integer(one_model$BTP_BUND_spread)
one_model$bank<-as.factor(one_model$bank)

str(one_model)
head(one_model)
table(one_model$bank, one_model$year)
any(table(one_model$bank, one_model$year)!=1)


# Transform data in panel
library(plm)
empirical_model<-pdata.frame(one_model)
attach(empirical_model)
Y<-cbind(ULR_state, ULR_banks, ULR_corporate)
X<-cbind(LEV, ROA, TIER1, SIZE, BTP_BUND_spread)


# Run the Fixed Effect model
FE_state <- plm(ULR_state ~ alfa_i + lag(BTP_BUND_spread,1) + lag(LEV,1) +
lag(ROA,1) + lag(TIER1,1) + lag(SIZE,1), data = empirical_model, index =
c("bank","year"))
summary(FE_state)
```

```
FE_banks <- plm(ULR_banks ~ alfa_i + lag(LEV,1) + lag(ROA,1) + lag(TIER1,1) +
lag(SIZE,1), data = empirical_model, index = c("bank","year"))
summary(FE_banks)

FE_corporate <- plm(ULR_corporate ~ alfa_i + lag(LEV,1) + lag(ROA,1) +
lag(TIER1,1) + lag(SIZE,1), data = empirical_model, index = c("bank","year"))
summary(FE_corporate)


# Run the Random Effect model
RE_state <- plm(ULR_state ~ alfa_i + lag(BTP_BUND_spread,1) + lag(LEV,1) +
lag(ROA,1) + lag(TIER1,1) + lag(SIZE,1), data = empirical_model, model =
"random")
summary(RE_state)

RE_banks <- plm(ULR_banks ~ alfa_i + lag(LEV,1) + lag(ROA,1) + lag(TIER1,1) +
lag(SIZE,1), data = empirical_model, model = "random")
summary(RE_banks)

RE_corporate <- plm(ULR_corporate ~ alfa_i + lag(LEV,1) + lag(ROA,1) +
lag(TIER1,1) + lag(SIZE,1), data = empirical_model, model = "random")
summary(RE_corporate)


# Run the Between Estimator
BW_state <- plm(ULR_state ~ alfa_i + lag(BTP_BUND_spread,1) + lag(LEV,1) +
lag(ROA,1) + lag(TIER1,1) + lag(SIZE,1), data = empirical_model, model =
"between")
summary(BW_state)

BW_banks <- plm(ULR_banks ~  lag(LEV,1) + lag(ROA,1) + lag(TIER1,1) +
lag(SIZE,1), data = empirical_model, model = "between")
summary(BW_banks)
```

```
BW_corporate <- plm(ULR_corporate ~ alfa_i + lag(LEV,1) + lag(ROA,1) +
lag(TIER1,1) + lag(SIZE,1), data = empirical_model, model = "between")
summary(BW_corporate)

# Hausman test for fixed versus random effects model state
phtest(RE_state,FE_state)

# Hausman test for fixed versus random effects model banks
phtest(RE_banks,FE_banks)

# Hausman test for fixed versus random effects model corporate
phtest(RE_corporate,FE_corporate)

# Hausman test for between versus random effects model state
phtest(RE_state,BW_state)

# Hausman test for between versus random effects model banks
phtest(RE_banks,BW_banks)

# Hausman test for between versus random effects model corporate
phtest(RE_corporate,BW_corporate)
```

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