Department of Corporate Finance

Course of Asset Pricing

Determinants of CDS spreads
Empirical Analysis over European Banks

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ACCADEMIC YEAR

2018/2019

Abstract

Using a sample of 853 quarterly observation from 20 European listed Banks, the analysis aims to examine the determinants of the Credit Default Swap spread according to two groups of variables. The first group constitutes the structural variables: leverage, volatility and risk-free rates while the second one is represented by the CAMELS indicators (capital adequacy, asset and management quality, earnings, liquidity and sensitivity to market risk). First, the analysis finds empirical evidence towards the economical and statistical significance of both structural and CAMELS variables. Furthermore, it is demonstrated CAMELS indicators provide additional information beyond structural variables for banks' CDS spreads. It is also addressed the topic of the credit spread puzzle, according to which the structural variables fail to predict the whole credit spread variance. The model discovers that – within the sample observed – the credit spread puzzle remains an issue even after adding further firm-specific variables (i.e. CAMELS). Moreover, it is investigated the impact of the financial crisis – intended to be the sovereign debt crisis – upon the structural model variables. The analysis finds that the leverage variable has a stronger impact on CDS spreads during crisis period while volatility has the opposite effect.

The analysis is run through an unbalanced panel data regression by the STATA software. Data are provided mainly by the Bloomberg and Thomson Reuters Datastream terminal.

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1. Introduction

Financial institution had an important role during the recent financial crisis experiencing a big downturn throughout this period. After the crisis, the attitude towards banks has changed: many efforts were addressed to any warning system that could help prevent or avoid other negative shocks to happen again.

One indicator could be represented by the Credit Default Swap (referred to as CDS from now on) spreads, which reflects the likelihood of a firm to go bankrupt. It is a derivative contract where the “protection buyer” periodically pays an amount – called spread – to the “protection seller” who, in change, repays the counterparty losses when a credit event occurs, the latter is specified in the contract but the most common one is default. The underlying asset of the credit default swap contract is the corporate bond.

Therefore, CDS contract spread levels provide important insight regarding a firm financial soundness position. Many researchers have focused their attention upon the CDS of industrial companies. However, it is interesting to analyze how this derivative apply to the banking industry given the systematic importance of these entities and their role during the financial crisis. For these reasons, this thesis aims to provide the literature with some empirical evidence of what are the CDS spread determinants upon European Banks.

The sample consists on European banks, due to data availability reasons the model picked just the listed ones. The time period analyzed goes from 2008 to 2018 which is slightly different from what the current literature provides, in fact most papers that address this topic end their sample in 2014.

This thesis wants to identify the determinants of the CDS spreads for European bank using pooled linear regression models. The literature framework regarding the credit models lies on the product of Merton studies according to which default depends upon three main variables: leverage, asset volatility and the risk-free interest rate. Researchers commonly use the structural model to price credit risk within companies as the three variables stated above represent the main determinants of default likelihood. Benkert (2004) in his study showed how the structural model variables can be applied to CDS pricing as well.

Traditionally the literature prefers to focus upon industrial companies to analyze credit theories, this is because banks have their specific business model and must meet some regulatory requirements especially in terms of debt and capital levels. For this reason, the leverage variable should have a low variance that may affect the quality of the study and the explanatory power of the model in general.

However, banks can still decide to hold more capital than the level required by law in order to protect themselves from external shocks. Therefore, banks can have optimal leverage ratio – besides the regulatory requirement thresholds – like the other industrial companies do. It is then interesting to assess whether leverage has an impact within financial institutions' credit risk framework and analyze if this impact differs during periods of crisis or not.

The study addresses the topic of the credit spread puzzle according to which the structural variables – developed within Merton model (1974) – fail to explain the whole variability of the credit-spread. In order to do that the model runs different regressions applying a stepwise approach.

First, it is run a regression with just the three structural variables as the independent regressors. After finding proper proxies to express each variable in a way that fits the regression structure, it is found that each variable is statistically and economically significant for the CDS of the banks in the sample. The coefficient values – particularly their signs – are robust to model specification. The adjusted R-squared for the regression is 42,75% indicating that the structural model variables explain just a portion of the credit-spread variance consistent with what the credit-spread puzzle theory suggests.

Afterwards, further variables are added into the model to examine whether they provide additional information with respect to the structural variables and if the credit-spread puzzle, in the sample, is still an issue even after adding more firm-specific factors. Those variables are the so-called CAMELS indicators which are traditionally used by bank regulators to rate a bank's financial position. The study picked CAMELS framework since it is strictly related to banks' business models, therefore they could help to reduce the credit-spread puzzle.

A CAMELS rating system is an acronym for the 6 variables that carries-out: capital adequacy, asset quality, management quality, earnings, liquidity and sensitivity to market risk. Each one is developed through a proper proxy, also helped by the contribution of Hasan et al. (2014) which apply those indicators within their model.

The regression with just CAMELS indicators shows that, except for management quality, all the variables are statistically and economically significant. The coefficient signs define the relationship with the dependent variable and each one of them are in line with the expectations.

It is then run another regression with both groups of variables, showing that those are significant from a statistical point of view, except for management quality. The most interesting feature in these results regards the adjusted R-squared, equal to 49,22%. Thus, the inclusion of CAMELS variables in the study improves the model fit of 7 percentage points suggesting that they do provide complementary information with respect to the Merton model variables.

Furthermore, this study enables to state that, even if the models' explanatory power has increased, there is still a robust percentage of variation in the dependent variable that is not explained. For this reason, the credit-spread puzzle remains an issue within the sample considered and according to model specifications.

It is also examined the impact of the sovereign debt crisis over two indicators (leverage and volatility) by adding a dummy variable. It is found that leverage has a stronger negative impact during crisis than non-crisis period while for volatility is valid the opposite.

This study will then contribute to the literature in several ways. First, it delivers evidence to the applicability of structural variables for pricing banks' CDS spread while the contribution upon credit risk mainly focuses on industrial companies because of business model characteristics. It also provides the authorities with a new warning system – the Credit Default Swap spread – that can be useful during monitoring activities upon the banking industry's stability. It is then important to understand what the determinants of these spreads are, since they can be used as warning alert that triggers the intervention on banks' supervisors.

The work is organized as follow. Chapter 1 provides an overview of the Credit Default Swap contracts from a theoretical point of view. Afterwards, chapter 2 focuses upon the model specifications explaining how each variable is calculated and it gives an economic intuition about the expected relationship with the CDS spread. In conclusion, after providing summary statistics and a correlation matrix to better describe the dataset used, chapter 3 will show the regression results and explain them in relation to the hypothesis developed.

2. Overview of Credit Default Swap

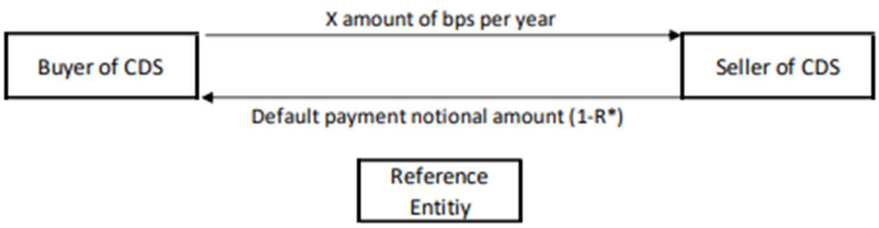
Credit risk is one of the most important topics among the whole finance literature due to the direct connection with the financial soundness of the world banking systems. Credit Default Swap contract still represents a controversial security among the derivatives market. On one hand, their supporters analyze it as an efficient tool to manage and deal with credit risk; on the other hand, the opponents assess the high riskiness of this asset given its speculative usage that may influence government default. The savvy investor Warren Buffet refer to CDS as "weapons of mass destruction" (Berkshire Hathaway Annual Report, 2002).

For this reason, both institutions and regulators are seeking for the right way to measure and manage this risk in order to forecast some downturns that may have systemic effects in the whole economy, especially when it comes to CDS over bonds issued by banks.

In recent years, the derivative market has developed some tools to manage credit risk. Credit derivatives allows an entity to transfer credit risk from one party to another, the most popular credit derivative is indeed the CDS.

The first Credit Default Swap contract was developed by J.P. Morgan in the early nineties. This was a response to the increasing demand of transferring credit risk between entities. As a matter of fact, CDS is a derivative financial contract that allows an entity to purchase an insurance against a predefined credit event in change of a fixed periodical income. On the other side, there is a "protection seller" that collects - either annually or semiannually - an income and is committed to pay a certain amount when a credit event occurs.

Figure 1: CDS Contract



Source: Determinants of European Bank CDS Spreads

Figure 1 shows how a plain vanilla CDS works in practice. Being a buyer of a CDS means that you are buying protection against default of a reference entity, this protection costs an X amount expressed as basis points of a notional value. On the other hand, the seller collects periodically the cash flows and offers the payment in case a credit event occurs. R* represents the recovery rate, which is the percentage of the face value of debt showing the portion of defaulted debt that can be recovered. The amount of money the protection seller must pay is equal to the difference between the par value of debt and its value after recovery. For this reason, the CDS premium is considered an indicator of credit risk for the underlying entity.

Table 1. Credit Default Swap transaction

Protection seller	Protection buyer
Does not own the underlying credit instrument	Owns the underlying credit instruments
Sells protection on a credit position	Buy protection against a credit event
Long credit exposure	Short credit exposure

Table 1. shows a recap of the main feature regarding the two counterparties of a CDS contract. Within this scheme, it is important to consider the cash flows' direction. Since in this contract there are two main cash flows:

1. From the protection seller to the buyer there is a settlement payment in case a credit event occurs;
2. From the protection buyer to the seller there is a periodically premium paid.

CDS contracts can be seen as an insurance against the default of the underlying entity, where the protection seller pays the due sum if the credit event occurs, while the protection buyer makes regular payments to the former based on the settled credit default swap premium (Ericsson et al., 2009). Unlike the insurance contracts, the CDS buyer does not have to hold necessary the underlying asset to get the remuneration, meaning that a market agent can speculate on a credit risk he is not actually exposed to, this situation may results in some dangerous finance behavior leading to some economy downturn, for instance.

Credit Default Swap contracts can be divided into three categories: single-name CDS, CDS indices and basket CDS:

1. Single-name CDS, according to the European Central Bank, is a contract that provides protection for a single corporate/sovereign reference entity.
2. Amato and Gyntelberg (2005) define CDS indices as an insurance against "default risk on the pool of names in the index", an important feature of this contract is that the credit event does not terminate the contract itself.
3. Hull and White (2000) describe the basket CDS contract as involving multiple reference entities, the payoff occurs once the first of these entities' defaults.

The credit event represents the instance that triggers the payments from the protection seller, this event is normally predefined in the contract between parties and it can be of different types. The failure of an entity to meet its obligation towards the reference firm is defined as credit event. Another example of a credit event could be the delay in payments as well.

Table 2 below provides a summary of the main credit event triggers.

Table 2. Credit Event eligible for a CDS contract

Bankruptcy	Reference entity becomes insolvent and it is not able to pay back its debt.
Miss payment	Reference entity does not meet its obligation at maturity (i.e. doesn't pay the due sum).
Debt restructuring	Reference entity's debt structure is modified in a way that penalize its creditor.
Non-execution of one obligation	Reference entity's obligation became due before the predetermined date.
Moratorium	Reference entity refuses its debt; it doesn't pay both interests and capital.
Downgrading	Reference entity credit rating gets worse from a proper agency.

Source: International Swaps and Derivatives Association - ISDA

An important aspect of the CDS contract is represented by the premium (also called spread), which is quoted in basis point of a certain notional amount. For such reasons, this spread is an indicator of the underlying entities' credit risk. For example, let's assume that the notional amount is $10Million; stating that the 5-years CDS spread issued by Goldman Sachs went from 115bp to 138bp means that the protection buyer will now pay $138,000 instead of $115,000 to guarantee $10M of debt against default (Hasan, Liu, Zhang, 2014). The increase of the premium means that the likely of Goldman Sachs default has increased, for this reason insure against a credit event is now more expensive, since default is now more likely to occur.

This thesis aims to analyze what determines the level of the CDS spread with respect to European Banks, given both the CDS premium's predictive power of a firm's financial distress and the systemic importance of bank institution.

Many researchers have investigated alternative proxies to measure a corporate credit risk, the most common proxy besides the CDS Spread is the so-called Credit Spread; the latter is defined as the difference between corporate bond yield and the correspondent risk free rate. In other words, the spread represents the excess interest rate earned if the company does not default and the investors holds the bond to maturity.

The literature defines the CDS spread as a better corporate credit risk estimator than the credit spread. Hull et al. (2004) argues that the CDS has an easier pricing nature, since it does not need any assumption (i.e. risk-free rate) for the credit spread calculation. Furthermore, Norden and Weber (2004) assess that CDS market has more predictive power on credit rating especially in downgrade movements. Plus, CDS market is also more sensitive to the stock market than the bond market.

2.1 CDS market

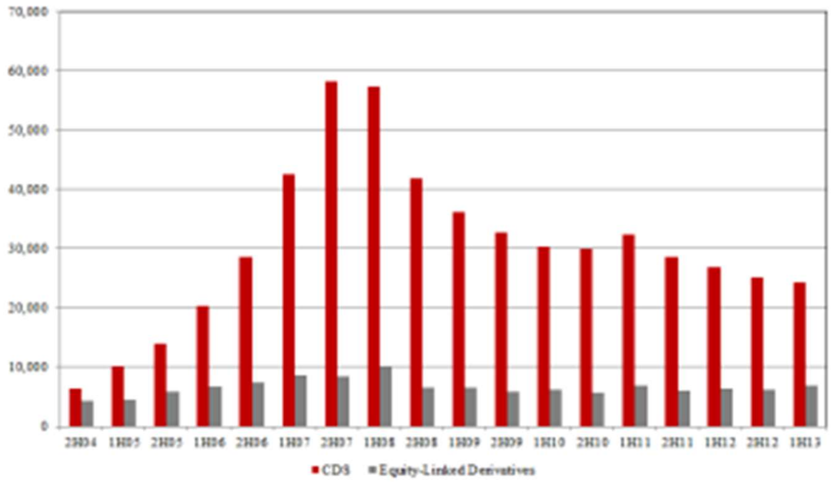
Credit Default Swap contracts are traded in the OTC market; institutional and legal guidance are given by ISDA (International Swaps and Derivatives Association). The ISDA role was indeed crucial for the development of the credit derivative market, since it had provided a standardize contract in 1992 that enabled OTC market participants to have a fully documented, but flexible at the same time, contract to start the negotiations with.

Few years afterwards their first creation in 1994, CDS market size was still modest in terms of notional amounts outstanding. The first exponential growth was experienced from the early 2000s straight to the financial crisis.

One of the main reasons below this expansion was the first ISDA’s sets of standardized contracts that enables counterparties to have a proper structure for their settlements, thus there was an increase in the incentive to settle for these contracts. In 2004, the total notional amount of CDS outstanding was $6 trillion, the market kept growing fast until reaching a value of $60 trillion just prior the beginning of the financial crisis in 2007.

CDS contracts had a crucial role in the credit crisis, for this reason the market size dropped considerably after Lehman’s bankruptcy. The decline was also experienced in other derivative markets, but not with that intensity. After the crisis period, the CDS market size remain to high level, in fact in December 2013 the level was $21 trillion.

Figure 2: CDS market size level



Source: Credit Default Swap: A Survey (Augustin et al. 2014)

Figure 2 shows the level of CDS market size from 2004 to 2013. It is interesting to see how sharp the development of this amount was in the years previous the financial crisis, in which the market had witnessed its highest values (i.e. second half of 2007 and first half 2008). After the bubble burst the size started to decrease but still higher than 2004 – 2006 level, i.e. pre-crisis period.

Since the '90s, CDS market had been growing up really sharply in terms of volumes traded. This trend continued until the big financial crisis 2007 – 2008. The market size and its predominant role during the crisis highlighted the need to increase both transparency and regulation in order to avoid negative outcomes and control the market itself. Since then the market witnessed some changes: its market participants reduced their exposure and redundant contracts were eliminated. Afterwards the regulatory framework was focused on the contract standardization, higher disclosure duties and margins requirements were asked as well.

After a sharp increase in the period prior the financial crisis, CDS market started to shrink very fast. This downturn was widespread since it encompassed a reduction both in the single-name and multi-name contracts. Such trend is observable through the market value of the outstanding position, which embraces the contract switching cost at the current market price. While notional amounts reflect the protection seller's maximum potential exposure towards the buyer, the gross market values provide insights regarding the current credit risk exposure.

Besides the notional amount, another massive reduction concerned the inter-dealer position. According to the quarterly BRI (International Banking Regulation) press release (June 2018), inter-dealer contracts have been reducing more rapidly than the market itself, moving from the 57% of notional amounts in 2011 to barely 25% at the end of 2017.

Those data are mainly due to the development of CCP (Central Counterparty Clearing) within the market, thanks to several factors:

1. The intervention of a CCP as counterparty between intermediaries;
2. Notional amount reduction due to a multilateral netting from CCP activity;
3. Contraction of the inter-dealer underlying activity.

One of the CCP most important activity is to net symmetric counterparty's position, which reduced the notional value of the outstanding contract in the market. Thanks to the netting operation, intermediaries gain both a reduction on the mandatory margin and a more flexible financial leverage requirement. This activity concerned more the multi-name contracts, as a matter of fact, those contracts are more standardized thus it is easier to net positions. Furthermore, in some regulatory frameworks like EU and US is mandatory to net CDS indices.

The after-crisis CDS contracts' decrease has affected the risk exposure compositions as well. A credit default swap contract implies two major risk categories:

1. Credit risk of the underlying entity;
2. Counterparty risk borne by the protection buyer.

Overall, both kind of risks reduced. As far as it concerns the underlying credit risks, those were moved towards sovereign debt titles and portfolios with a better credit rating. The netting activity, on one hand, helped reducing counterparty risk.

In the period following the crisis, it has increased the notional value among sovereign entities. Still according to the quarterly BRI press release, it went from $1,600B in 2007 to $ 3,300B in 2013. This data suggests the importance regarding the current solvency in the euro area across 2011 and the first half of 2012. Furthermore, the short sell ban upon sovereign titles introduced by Germany in 2010, and EU in 2012, may have pushed investors to replicate those expositions by entering a CDS contract.

Despite the increase attention towards sovereign debt derivatives, the non-sovereign entities still represent the major share of the market. Within this market share, the increase of index products helped moving away from the exposure to the single financial and non-financial company. This situation has leaded to a better credit quality of the entity underlying a CDS contract.

Overall both CCP and the standardization process had helped to reduce credit and counterparty risk. The gross exposures had decreased thanks to the netting activity which was easier after the standardization process. Even if the counterparty risk is assimilated by the CCP, still several security measures were introduced to reduce risk such as guarantee funds, margins level requirements and both asset and reserves obligations for CCP.

2.2 CDS and the financial crisis

Credit Default Swap contracts are commonly associated with the recent financial crisis. Those are thought to be strictly correlated with what happened in the financial markets between 2007 and 2008; even though there is no such prove in favor of this assumption.

A prominent role in the crisis was played for sure by the banking sector, one of its major players was in fact the investment banking Lehman Brothers Inc. which went bankrupt on September the 15th, 2008. As a matter of fact, Lehman and the insurance company AIG (American International Group) – bailed out by the government – were strongly involved in CDS sector.

As said before, CDS represents an OTC derivative contract thanks to which the operators can isolate, manage and transfer the credit risk within a reference entity. This latter feature may have also negative repercussions as well: in fact, a CDS contract can also spread a specific credit risk in a way that is tough to predict and control – the over the counter market is based on a contract stipulated between two parties, thus it is difficult to track each transaction occurred within this market. Another collateral effect is that uncertainty is spread creating speculative opportunities that generates skepticism towards the whole financial sector. It creates problematic incentives in which an operator can make profits out of a company's default, breakdown of the real-estate market or the bankruptcy of a whole country as well.

Even though the common opinion has accused the CDS to be the "worst evil instrument of the third millennium", it is studied recently how the first causes of the subprime crisis first and the sovereign debt crisis afterwards were mainly due to two causes:

1- Macroeconomic factors: credit bubble; FED monetary policy and American housing bubble;
2- Microeconomic factors: development of "non-traditional mortgages"; new financial innovation and securitization practices.

Besides those factors, the social behavior developed during '80s and '90s helped the financial crisis to take place. On one hand, there was the extreme capitalism wave which can be summed up by the common expression "Greed is good"; on the other hand, another expression developed that period was "I'll be gone, you'll be gone" which is strictly related to the securitization and the moral hazard issue. This sentence highlights the mechanism through which the mortgages where locked up and sold thanks to the variety of financial instruments that had been created during that period.

The mechanism consists on market operators that created a chain in which they sell securitized sub-prime bonds gaining a commission; the next operator in the chain still sold this securities to the clients, which were not aware about what was going on and relied on both the intermediaries and the credit rating agency which kept assessing those bonds were rock-solid. Everything was made in order to gain the highest fees possible without even considering the quality of the assets sold.

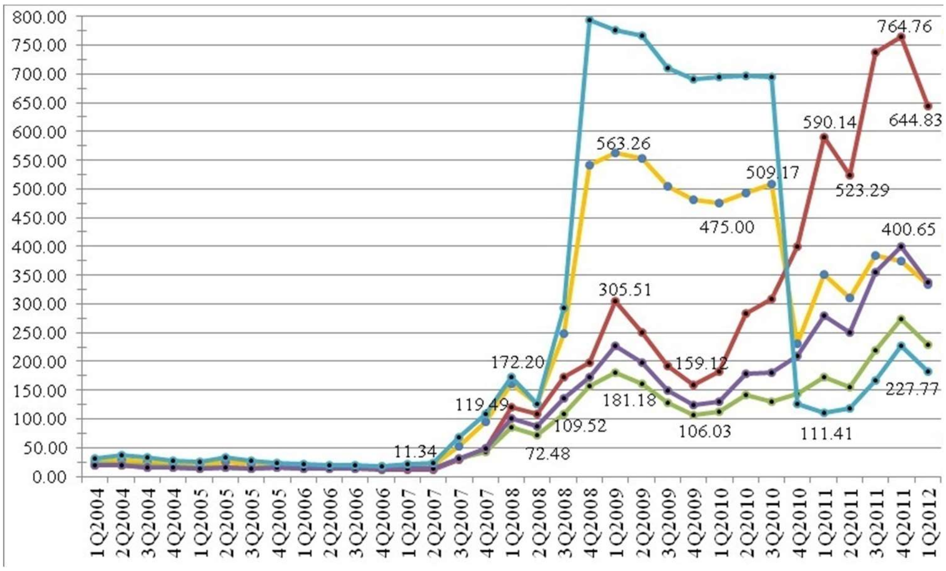
Therefore, the financial crisis is a highly complex issue that it is a mistake the commonly idea to consider CDS as the main cause of what had happened. One negative outcome can be the fact that the CDS may have aggravate the negative effect of a crisis, but this must be proven anyway. Trying to make a link between these instruments and the financial crisis, what is indeed very interesting to see is that recent studies affirm the CDS contracts to be a very powerful indicator of a bank financial soundness.

CDS spread represents them as an easy and direct measure of a company's credit risk. Since the bank's CDS spread level has reached their highest levels immediately before their failure, markets participants recognize them as a reliable indicator for the riskiness of an investment. The financial crisis has made this derivative instrument a crucial parameter to understand, value and monitor the solvency level of a reference entity and the reliability of their bonds.

For this reason, the purpose of this study is to analyze carefully which are the drivers of the premium upon CDS over the European Bank system in order to provide the current literature with some insight regarding this powerful economic indicator.

The mechanism is quite straight forward: higher is the probability of a credit event to occur, higher will be the spread quotation. This is one of the best features of the CDS contract: they allow to predict in advance the default probability of an entity.

Figure 3. CDS Senior 5-Year Spread level



Source: ALVEC - 2019

Figure 3 shows the level of the CDS Spread for several banks: Anglo-Saxon banks (yellow), PIIGS banks (red), German and French Banks (green), European Banks (purple), US Banks (blue).

One interesting feature that emerges from the graph is that CDS spread follow a similar pattern within the period considered (2004 – 2012); meaning that each quotation of the analyzed banks had a pattern influenced by the market they were listed. As a matter of fact, it is interesting to see how sharp the increase of the spread was after bankruptcy/bail-out of Bear Stearn, Lehman Brothers and AIG. Furthermore, it is important to highlight the increase witnessed in PIIGS and Eurozone countries after the Greek sovereign debt crisis.

So, the CDS spread trend confirms the thesis according to which it represents a valid riskiness indicator, since they can absorb immediately market information and consequently move.

For this reason, regulator and market participants must pay more attention to the behavior of a bank CDS spread, in order to promptly assess a risk profile first to the single bank and then to the general financial system.

Thus, it is important to leave this market free to act since some restriction may reduce drastically their quality to be good solvency predictors. However, it is still crucial to increase the transparency and the disclosures regarding these contracts, to intervene promptly if something is going on. For instance, it can be helpful the establishment of an ad-hoc Clearing House that may contribute to the development of the market itself.

Once understood the importance of the CDS spread predictive capacity, this thesis aims to analyze the determinants of those CDS premium in order to provide the literature with some insights regarding the main factors that affects the level of a bank financial soundness' determinant such as the credit default swap premium. The focus will be upon the European banks.

2.3 Credit Risk models

When it comes to pricing a credit default swap contract (i.e. defining its premium), the existing literature deals with two main models: structural model and reduced form model. The latter "treats default as an unpredictable even governed by hazard rate process" (Naifar and Abid, 2005) which will be described later in this chapter.

On the other hand, structural model assesses that default occur when the value of a firm's assets falls below a given threshold, normally expressed as a function of the outstanding debt (Collin – Dufresne 2001). Even though there are still big differences between the two models, they both belong to the no-arbitrage analysis of Black-Scholes-Merton (1974). According to Ericsson, the reduced form models doesn't explicit the drivers of the defaultable securities' prices while the structural model applies firm specific variables to the default process, such as leverage, asset volatility and interest rates.

Reduced form models represent a more recent method for credit risk pricing, it represents the default event as a random one based on factor that are not related with firm's characteristics. Since this model does not directly link the default event with a firm's fundamentals, lots of critics were advanced towards this approach.

Differently from the reduced form model, the structural one treats the default event as an endogenous process as it is explained as a function of firm's fundamentals.

2.3.1 Structural model

The biggest intuition below Merton model is to see firm's equity as a call option on its assets. Thus, the equity value is calculated through the Black-Scholes-Merton option-pricing model, intended to be a call option where the underlying is represented by firm's assets and the strike price of the call is the face value of the debt. Default happens when the call option is out-of-money meaning that the firm's asset value is lower than the face value of the debt.

For this reason, it is very important to consider some firms fundamentals such as leverage and asset volatility. In fact, the leverage becomes a proxy for the default threshold and the volatility may represents the likelihood to hit this threshold. When either the leverage or the volatility increase, then it increases the probability of default as well and the CDS premium consequently rises. The importance of the Merton model is that it includes in the credit risk theory some firm-specific factors such as leverage, volatility and the risk-free rate.

Merton's structural model is developed upon the following assumptions:

- Liabilities are represented by a Zero-Coupon Bond with face value of k maturing in T;
- No intermediaries' payments are made until maturity (Dividends, Coupons etc.);
- Probability of default is the probability that the Assets fall below Liabilities at maturity T;
- Asset value follows a lognormal distribution meaning that the logarithm of the asset follows a normal distribution.

From a more analytical point of view, it can be considered a company that in time t is financed by Equity and Debt: $A_t = E_t + D_t$. Where debt is a zero-coupon bond maturing in T (T > t) and strike price, K.

- If A_T > K, then debtholders will receive the full amount K at maturity. And shareholders will receive (A_T – K).
- If A_T < K, then debtholders will claim on firm's assets and receive A_T while shareholders won't receive anything.

Following the two scenarios possible, the Equity and Debt value in T takes the following value:

$$E_t = \max(A_T - k; 0); \; D_t = \min(A_T; k)$$

That Equity formula describes the payoffs of a European Call option, on the underlying asset A, with strike price K at maturity T. Therefore, Merton's intuition lies upon this latter passage where the Black-Scholes option pricing approach is applied in the credit default process.

The Black-Scholes formula takes the following shape (t is assumed to be today, i.e. t = 0):

(1) $c = S_0 \, N(d_1) - K \, e^{-r*T} \, N(d_2)$

(2) $d_1 = \frac{\ln\left(\frac{S}{K}\right) + (r + 0.5*\sigma^2)*T}{\sigma\sqrt{T}}$

(3) $d_2 = \frac{\ln\left(\frac{S}{K}\right) + (r - 0.5*\sigma^2)*T}{\sigma\sqrt{T}}$

The N within the European call formula represents the cumulative distribution function for a standard normal distribution. The call formula represents the stock price minus the discounted strike price adjusted by the standard cumulative distribution function.

The Merton intuition is to consider N $(-d_2)$ the probability for the option to be out-of-money in the risk-neutral world. Merton model is defined structural because it considers firm's value (S/K) in formula (2) to measure default probability.

Starting from today, t, the model wants to simulate the firm's growth until maturity T in order to compute the probability to fall below the threshold K – debt strike price. $\text{Ln}\left(\frac{S}{K}\right)$ measures the percentage the firm's value must lose to hit the threshold and go default, while the second part of the numerator $(r - 0.5 * \sigma^2) * T$ tells how much it will grow until maturity; r represents the assets' expected return while σ^2 represents the volatility.

The denominator, instead, is an operation aimed to standardize the value in order to rely upon the proper statistical tables. Having a value of d_2= 1.50 means that "the expected value of the firm is 1.50 standard deviation above default"; intuitively it can be seen as the distance to default.

Furthermore, it is assumed that the firm's possible values at maturities follow a normal distribution. Thus, taking N $(-d_2)$ will represent the probability to end-up below this threshold. It is then the probability of default in T, measured in t.

This model depends on the Asset volatility, while the equity value is often observed in the market. The usual approach is then to estimate the assets' value and volatility σ through the Black-Scholes call-option formula.

$$E_t = \text{BSCall}\ (A_T, \text{K}, \text{r}, \text{T}, \sigma)$$

K and T are defined by the firms' debt structure.

2.3.2 Reduced-Form model

The core of the structural model approach lies upon nature of the assets, their riskiness profile. On the other hand, the reduced-form model builds different assumption from the structural one. Those are the following:

1. Company's ZCB trades in a frictionless market;
2. Rf is stochastic;
3. State of the model can be driven by a macro-economic variable matrix X_t;
4. Company can default at any time before maturity T;
5. Company default represents an idiosyncratic risk;
6. Loss Given Default is a percentage.

Starting from these assumptions it can be possible to point out the major differences with Merton structural model. First, the structural model assumes that just assets are tradable, not even the equity while the reduced form carries out the bond trading as well.

Rf is stochastic meaning that it can change and take different values, in this way it takes into consideration the interest rate risk not considered in the other model where it is treated as a constant. Even if the debt is a ZCB, the default can occur anytime; in fact, in the reduced-form what matters is the cross-default which means that a company can default not just on a bond. The state of the economy, which describes the model, is made up by different vectors of macroeconomic variables such as GDP, employment etc. The economy could be then described by different cycles and the probability of default is more likely during economy's downturns. The structural model, instead, focuses just upon the balance sheet variables when computing the credit risk.

On the other hand, the company default is an idiosyncratic risk. The probability of default is driven by macroeconomic variables, but the default is an idiosyncratic event that changes between companies. The Loss Given Default is express as a percentage and strictly related with the business cycle.

Nowadays many practitioners use the reduced form more than the structural one. As a matter of fact, this model lies upon more realistic assumptions than the structural one. Those rating agencies that still applies the structural approach tents to reduce the time-horizon in order to meet the coupons date and treat them as a ZCB.

This comparison may have highlighted some important limits of the Merton's structural model which can be considered the starting point for what this thesis address to as the credit-spread puzzle, according to which the structural model variables fail to predict the whole variance in the credit spread. A deeper analysis of this credit puzzle is run in the next paragraph.

This study aims to first consider those structural model variables as the independent variables of the regression. The purpose is to analyze how those variables relates to the spread of the European bank CDS and their explanatory power. Afterwards, new variables (CAMELS indicators) will be added in the regression to check how they fit the model and whether there is an improvement in the explanatory power of the model with these variables as well.

As a matter of fact, Collin-Dufresne et al. (2001) find that variables that theoretically explain the spread changes have limited explanatory power. For this reason, researches started to combine different kind of variables in order to explain changes in the credit spreads. Particularly, Avramov et al. (2007) combined both common and firm-specific factors to describe more than half of the credit-spread changes. Many researches have highlighted the importance to mix both accounting and market-based data to describe changes in the spread providing the model with higher explanatory power.

2.4 Credit Spread Puzzle

The Merton's structural model represents the best theoretical framework to study credit risk and price corporate bonds as well. There are some findings according to which after matching historical default, recovery rates and equity premium, they fail to predict the actual credit spread, due to the so called "credit spread puzzle".

In other words, the models are not able to explain why they fail to predict the high excess return – over the risk free rate – that a corporate bond provides to its owners. Chen, Collin-Dufresne and Goldstein asses that this credit-spread puzzle can be explained through the introduction of other factors, like the common systematic risk factor, that may explain the equity-premium puzzle.

This concept lies on the fact that corporate bonds' spread – intended as the difference between the corporate bond yield and the government bond risk free rate - is sometimes wider than what suggested by just the default losses. Since the credit spread is intended to be the compensation for bearing a specific firm's credit risk, however it is difficult to define the relationship between spreads and the default risk itself.

The credit spread puzzle is the wide gap between spreads and the expected default losses. A common best practice is to consider that investors diversify perfectly the unexpected losses in a corporate bond portfolio, no matter what. By nature, the default risk leads to a highly negative skewed distribution of corporate bond's return. Under these circumstances, the full diversification is achieved through an extremely large portfolio. J. Amato and E. Remolona (2003) state that the origins below the credit spread puzzle might be the difficulty to fully diversify a corporate bond portfolio; hence the huge spread is due to an undiversified credit risk price that lead to a higher bond yield.

The credit spread analysis put its focus upon the systematic components common to all companies, the default-free interest rate. The resulting credit spread should reflect the financial soundness of the company that had issued the bond, assuming an economy without any transaction cost and tax effects.

Common empirical researchers explain less than 50% of the credit spread's variation due to the puzzle effect. For instance, Duffie, Saita and Wang (2007) provide a dynamic model to assess the credit risk of U.S. industrial firms. Their main finding is that, adding two market-based factors (3-month treasury bill rate and 12-month return of the S&P 500) provides a significantly explanatory power to forecast the default probability of a company assuming that those factors should be the only ones in corporate bonds' credit spread.

Collin-Defresne, Pierre, Goldstein and Martin (2001) attempted to explore this issue. The model address both variables related to default probability (leverage and asset volatility) and the change in short/long- term treasury bond yields and the return of the market portfolio (S&P 500 index). Their model can explain just the 25% of the corporate bonds' credit spread variation. The interesting findings is that the residual for company-specific regression are highly correlated across all bonds; resulting that one mutual factor can explain the 75% of the credit spread change.

Other researchers attempted to find the common non-default related factor that can explain the spreads for most of the companies. Studies focus on the tax differences between interest from corporate and treasury bonds and the difference in terms of liquidity below treasury and bond's markets.

The structure of this thesis aims to address the topic of the credit-spread puzzle approach. As a matter of fact, the model starts to explain levels of the European Banks Credit Default Swap spread by applying the structural model variables, it will be interesting to see the explanatory power of those structural model variables (leverage, asset volatility and risk-free rate). Afterwards, the model deals with the credit-spread puzzle issue by adding further factors that may provide more evidence to the CDS premium levels. Those added factor are the so-called CAMELS, which are 6 variables that represents the financial soundness of a credit institution:

- Capital adequacy
- Asset quality
- Management quality
- Earnings
- Liquidity
- Sensitivity to market risk

CAMELS variables are widely used by supervisory authorities to classify the bank's financial soundness and overall risk in order to predict failures. After having noticed whether those indicators have incremental explanatory power beyond Merton structural model variables, the model aims to understand if – in the sample – credit spread puzzle represents still an issue.

3. Research design

The study aims to understand what the determinants of the Credit Default Swap spread's level are. The starting point of the analysis is the intention to address the topic of the credit spread puzzle, according to which the structural variable fails to explain the higher excess return provided by a corporate bond. In order to do that, the regression model will apply a stepwise approach and see how the explanatory power is influenced by adding some CAMELS indicators to the normal structural framework. In the end it would be also clear if the credit spread puzzle remains an issue.

Thus, the analysis will start considering just the structural variables (leverage, asset volatility and risk-free interest rate) as the only independent factors of the regression. Afterwards, another regression is run by applying the CAMELS (Capital adequacy, Asset quality, Management quality, Earnings, Liquidity and Sensitivity to market risk) factors as the only independent variables.

As a recap the analysis that the study aims to perform is the following:

1. Regress CDS spread with Leverage, Asset volatility and Risk-free;
2. Regress CDS spread with Capital Adequacy, Asset quality, Management quality, Earnings, Liquidity and Sensitivity to market Risk;
3. Regress CDS spread with both groups of variables from the first two regressions.

Those first regressions will then provide some insights about the determinants of the CDS spread level. An important measure used to interpret the results is the R-squared. From a statistical perspective, R-squared measures the variability of data in relation with the accuracy of the statistical model applied. This number explains the dependent variable's variance with respect to the independent factors used in the regression. In a simple linear regression, R-squared is computed applying the square of the correlation coefficient:

$$R^2 = \frac{ESS}{TSS} = 1 - \frac{RSS}{TSS}$$

ESS: Explained Sum of Squares, which is the deviance explained by the model;

TSS: Total Sum of Squares, meaning the total variance.

RSS: Residual Sum of Squares, representing the residual variance.

R-squared is also known as coefficient of determination, since it reflects the percentage of variance in the dependent variables explained by the independent one. In other words, it represents the variance of the CDS spread level justified by the variance in the structural model variables, in case of the regression with just leverage, volatility and risk-free as explanatory variables. This measure is indeed very helpful for the whole result interpretation.

In accordance to the current studies and the credit spread puzzle framework, it is expected that the R-squared from the first regression does not explain the whole dependent variable. In other words, the structural variables per se should explain just a part of the variation in the CDS spread.

By adding another group of variables (CAMELS indicators) to the regression, the analysis aims to highlight the increase in the R-squared value, apart from the regression coefficient as well. This means that those variables do account when it comes to determine the likeliness of a credit event to occur; in other words, they contribute to define spread level of a CDS whose underlying is a bond issued by a European Bank. Thus, the credit spread puzzle exists and indicators of a bank financial soundness provide incremental information beyond structural variables to assess credit risk. In order to assess that, it is expected that the R-squared of the third regression is higher than the first one, with just structural variables.

Furthermore, the analysis wants to investigate the resultant coefficient in the regressions, to see whether those selected variables are statistically and economically significant. It would be interesting to see how indicators of a bank's financial soundness – CAMELS variables – relates with the premium of a CDS over a bond issued by the bank itself. This study utilizes some proxies to reflect the CAMELS indicators to fit the dataset.

The regressions are performed through a specific statistic software called STATA. This software automatically runs a hypothesis test in which the null hypothesis is that the vector coefficient is equal to zero. In order to have robust results, the results should reject the null under a predefine confidence interval, in the specific case by default is equal to 95%.

In order to see whether each variable has a statistical significance, it is utilized the t-stat provided by the program for each independent variable. The best practice suggests that this number should fall within the confidence interval – provided by STATA as well – or, in alternative, should be higher than +2 and lower than -2.

Apart from the statistical significance meaning of the whole variables, it is interesting to see the actual coefficient number in order to highlight some economic intuition below it. First, the sign of the coefficient is very important to assess the relationship between the explanatory variable and the dependent one assessing whether it is direct or indirect.

The structural model theory offers a robust background with respect to the first three variables applied by the model, for this reason the results are expected to be in line with what the theory suggests is the relationship with the Credit Default Swap spread. As far as it concerns the CAMELS indicators, there is no such active theory and literature that relates them with a bank CDS premium, for this reasons it will be interesting to see whether the results reported are in line with the economic intuition, that will be given later on in this chapter.

In conclusion, running the last regression – which comprises all variables together – enables the study to analyze if there will be significant differences with the former two, and how the coefficient will be when placed all in the same regression.

A correlation matrix calculation is also performed to understand the relationship between the whole variables in the model. It is important here not to see high correlation values since according to the Ordinary Least Square coefficient estimation those should be independent to each other. Another important aspect to understand in the matrix is whether there are some endogenous elements. In case two variables have very high correlation coefficient (i.e. closed to either +1 or -1), then it is possible that there is a third one that influence and drive those variables.

3.1 Data

The sample consists of 20 Listed European Banks, the choice to pick just the listed one is in relation with the availability of data since it is applied a quarterly frequency observation for each year. The period consists of 11 years as from the first quarter of 2008 to the end of 2018.

Thus, the overall number of observations should be equal to 880 composed as: 11 years x 4 (year frequency – quarterly) x 20 which is the sample size. Unfortunately, some data were not available for the whole sample but on the same time the study didn't want to exclude any variable. Therefore, for some banks it is taken off some year observations for which data were not available at all, leading to an unbalanced panel data regression with an overall number of observations of 853, which is still robust.

For some observations, it was found just annual data and a proper linear interpolation was performed to account for quarterly data estimation. For some ratio estimation, those were assumed to be slightly equal for the whole year period.

As said before the sample consists on listed European banks, either commercial or investment. At the very beginning the model took into consideration those banks that have CDS quote data available in the Bloomberg terminal. Afterwards, when it comes to collect data of the other variables it emerged some difficulties to find them at a quarterly frequency for the whole bank selected. Consequently, the choice is to go direct to the European listed Bank in order to deal with data at a quarterly frequency observation. The sample is divided as following: Belgium (1), France (3), Germany (1), Great Britain (2), Italy (5), Spain (3), Sweden (3), Switzerland (2).

Table 3. European banks in the sample by country

Country	Banks	Observation	Percentage	
Spain	BBVA	44	5,16%	15,47%
	Banco de Sabadell	44	5,16%	
	Banco Santander	44	5,16%	
Great Britain	Barclays	40	4,69%	8,91%
	HSBC	36	4,22%	
France	BNP Paribas	40	4,69%	14,07%
	Crédit Agricole	40	4,69%	
	Société Générale	40	4,69%	
Germany	Commerzbank	44	5,16%	5,16%
Switzerland	Credit Suisse	44	5,16%	10,32%
	UBS	44	5,16%	
Italy	Intesa Sanpaolo	44	5,16%	25,79%
	Mediobanca	44	5,16%	
	Monte dei Paschi	44	5,16%	
	UBI	44	5,16%	
	Unicredit	44	5,16%	
Belgium	KBC Group	44	5,16%	5,16%
Sweden	Skandinaviska	44	5,16%	15,12%
	Swedbank	41	4,81%	
	Svenska	44	5,16%	
Total Sample	20	853	100,00%	

Table 4. Number of observations in the sample by year

Year	Observation	Percentage
2008	45	5,28%
2009	72	8,44%
2010	79	9,26%
2011	80	9,38%
2012	78	9,14%
2013	79	9,26%
2014	80	9,38%
2015	80	9,38%
2016	80	9,38%
2017	80	9,38%
2018	100	11,72%
	853	1

Table 3 shows the constitution of the sample by country, Italy is the most represented one within this study. On the other hand, Table 4 differentiate the sample according to year. As the observation goes back in the years it is more difficult to find CDS quotes and quarterly balance sheet observation for the selected banks. Therefore, years 2008 and 2009 are the one with less observation in this study.

3.2 Dependent Variable

The study considers the senior unsecured 5-years maturity Credit Default Swap Spread contract to be the dependent variable. Meaning that the CDS contracts selected have the underlying assets represented by a 5-years maturity senior unsecured bond issued by the respective bank.

A senior bond is the one with the highest level of safety: in case the bank goes bankrupt, the senior bondholder will be the first to get refund. On the other hand, a senior bond provides the owner with a lower return that a subordinated one. A bond can be also classified in:

- Secured: the obligation is covered by specific firm's assets;
- Unsecured: not covered by any asset, but still the refund is earlier than a subordinated bond.

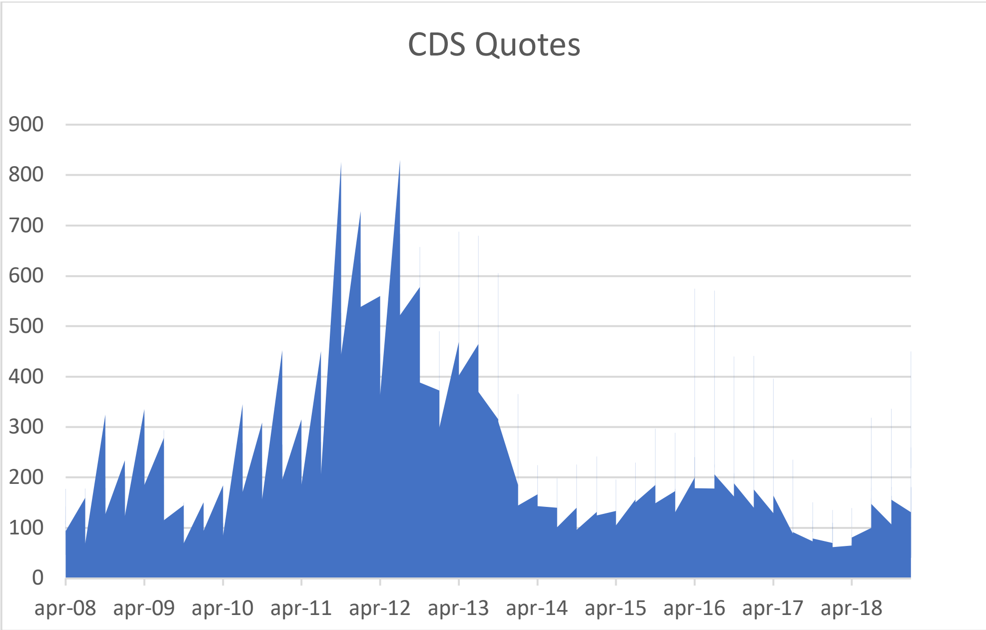
It is picked the unsecured because it is the most common one, thus it helped the data to cover the whole sample size considered.

Since CDS contracts are negotiated in the over the counter market, their maturities are flexible as well. Therefore, there is a wide spectrum of maturities available going from 10 moths to 10 years or even more. Although the most common maturity range is 5 years, the 5-year maturity contract is the most liquid one and it represents slightly the 85% of the whole CDS market. Furthermore, it is also the most frequently CDS's type traded as well. For these reasons, the study focuses his attention to this 5-year maturity type of contract.

CDS quotes are collected directly from the Bloomberg terminal, and it is observed the spread at the end of each quarter with respect to every bank within the sample. The first quote is taken at the end of the 2008's first quarter since before this date it was very difficult to find spread levels at all. The last date picked is the end of 2018, because the 2019 is not finished yet and the analysis didn't want to consider just 3 quarters for comprehensive and consistency issue.

Furthermore, it is important to highlight that the frequency chosen for the CDS quotes (i.e. level at the end of the quarter) is consistent and compatible with the accounting data availability, that have the same calendar date, and represents an important aspect of the CAMELS variables constitution. In this sense, there is time consistency between the data selected.

Graph 1. Distribution of the CDS spread



Graph 1 shows the chart of the CDS quotes – expressed in basis point - that constitutes the model's sample. First, it should be highlighted that the sample starts in 2008 when the financial crisis was about to take place, as a matter of fact Lehman brother went bankrupt on September of that year.

However, the crisis spread all over the world hit the Europe financial system through the well-known sovereign debt crisis that affected many countries, included in the sample as well. According to Lane (2012), the bond market started to show his first signs of crisis in 2010 with the widening of the Greek 10-year government bond yields. Since CDS and bonds are strictly related, the beginning of the Eurozone crisis is intended to be 2010. This is supported by the massive increase that the chart shows since 2010. Thus, the sovereign debt crisis has a time frame that goes from 2010 to 2012.

Since the sample is composed of European bank's CDS, Graph 1 shows a steep increase in the quotes during that period. An increase in the spread level represents a highly likeliness to go bankrupt reflecting the harsh times the European financial system had to face during that time. In other words, the protection buyer this time must pay periodically more money to the CDS counterparty to assure against a predefined credit event. In this sense, the data collected are in line with what expected from the historical issue during that period.

The post-crisis period goes from 2013 to 2018 witnessed an improvement of the economic system, thanks to ad-hoc financial policies run by the European Central Bank, Quantitative Easing policy was overall the most important one. As a result of the improved situation, the chart shows a decline in the CDS premia reflecting a better financial position of the overall bank system.

3.3 Explanatory Variables

Common literature, led by Merton (1974) studies, link credit spread issue with default losses. Therefore, many studies aim to test this model by applying proper proxies to account for the main determinants. Those variables account for both firm-specific factors – leverage or volatility of a firm’s assets – and market-based variables. Empirically what is shown is that the Merton’s structural variables have weak explanatory power alone. Thus, many studies, like this one, argue that by adding more variables it is possible to increase the explanatory power of the model providing further evidence to the Credit Default Swap Spread levels beyond the structural framework.

To address this issue, the model’s structure provides two groups of explanatory variables, and it applies a stepwise approach to run its regressions. Further, this chapter provides a detailed description of each variable selected and how it correlates with the CDS premium.

3.3.1 Leverage

It is commonly known that financial ratios are based on accounting standard and practices that may influence the reliability of data. Many time managers tent to use their accounting flexibility to highlight certain results under their mandate for instance or apply some accounting practices that may affect the reliability of data.

Still, Das et al. (2006) states that accounting data holds additional information not embedded into market-based models when it comes to credit risk. Anyway, the literature exposed many different types of leverage proxies to run a study upon credit risk: balance sheet ratios, market based financial leverage and stock return. For sure it is impossible to find a proxy that reflects all these potentially fields involved. In their paper, Dullman and Sosinska (2007) asses that the equity return is a measure that include insight about the firm’s leverage.

Of course, this measure is strictly sector-specific, thus it is important to considered also the banking sector landscape when it comes to leverage. Still Dullman and Sosinska state that balance sheet leverage ratios lose part of the explanatory power when applied to the banking sector, assuming that this industry has a very large off-balance sheet activity.

In general, it is true that the financial sector has a very specific leverage level. They have a different asset and liability structure when compared to industrial corporations; since they rely mainly on deposits to finance their activities. For this reason, their leverage ratio tents to be higher than the corporate industrial sector.

For sure leverage is a complicated issue when managing a company, specifically a bank. High levels of leverage mean that the firm can collect more deposits leading to high growth potential. But on the other hand, too much debt over equity can lead to a bankrupt. So, it is strictly related to the creditworthiness of a company, it is then expected that a high level of leverage lead to a higher intrinsic risk of the firm, thus higher levels of the credit default swap spread.

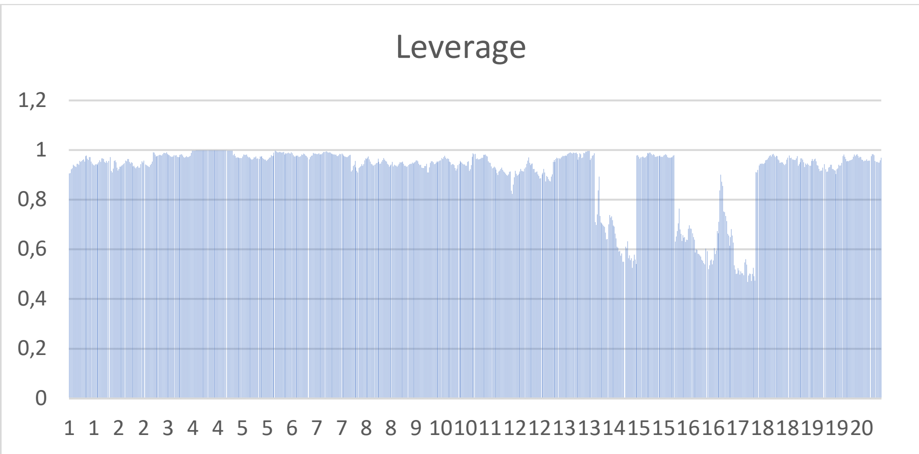
Differently for many studies that apply balance-sheet ratio (Chiaramonte and Casu, 2013) or those that apply the equity stock return as a proxy (Annaert et al., 2013), this study applies the formula provided by Hasan, Liu and Zhang (2014) to account for this variable:

$$Leverage = \frac{BV\ Liabilities}{(BV\ Liabilities + MV\ Equity)}$$

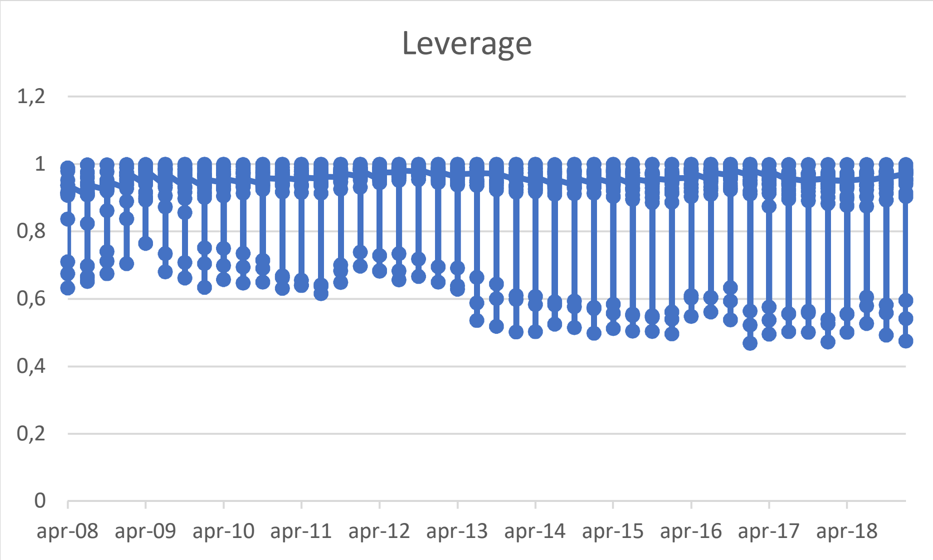
According to this formula, leverage reflects both balance sheet items (i.e. book value of liabilities) and market-based items (i.e. market value of equity). With this specific formula, a high value of Leverage reflects high level of debt, thus higher CDS premium so a positive relation should stand. Consequently, the coefficient for this variable is expected to be positive.

Since the banking industry has some strict regulatory requirements, the leverage variable may not be that exogenous. However, as said in the introduction chapter, there still might be some flexibility regarding the leverage decisions. Banks can decide to hold additional capital to better deal with economic downturns during crisis period.

Graph 2a. Leverage between banks



Graph 2b. Leverage across time



It is then important to provide further evidence regarding the variation of the leverage variable both cross-sectional (between banks in the sample) and across time. Graph 2a. provides evidence of the variance that occurs below banks selected while Graph 2b. considers the variation of those value across time. There is enough volatility that enables the study to consider this variable as an exogenous independent one.

All the book value numbers are calculated through the quarterly results provided by the Bloomberg terminal. The market value of Equity is instead taken from the Datastream Thomson Reuters software, always following a quarterly frequency.

3.3.2 Volatility

According to the structural Merton model (1974), another important determinant of the Credit Default Swap spread is the firm's asset volatility, which is very difficult to observe indeed. For this reason, it is crucial to find an available measure to proxy this important variable; the most common one is the equity volatility which is applied in this model as well.

In fact, Ito's Lemma theory suggests a positive relationship between equity and asset volatility. So, an increase in equity volatility results in an increase in the asset's value volatility; the latter one will then increase the probability of the asset level to hit the default threshold, expressed as a function of the current outstanding debt. For such reasons, it is expected a positive relationship between equity volatility and the CDS spread (i.e. positive regressor coefficient).

Equity volatility measures are taken form the Thomson Reuters Datastream which provided, on a quarterly basis, the 5 years historic volatility. This software applies a time horizon of 5 years to compute the volatility, at the end of each quarter it gives the volatility measure of the whole 5-year period ending that date. The volatility is computed as the standard deviation of price, measuring the dispersion around the 5 years average value.

3.3.3 Risk-free interest rate

The risk-free interest rate is the third and last variable within the Merton structural model. According to this framework, the risk-free represents the risk-adjusted drift of the firm value. Thus, it is intended to be negatively related to the CDS spread. As a matter of fact, interest rates are positively related to the economic growth and negatively to default probability.

However, current literature regarding this issue represents both type of connection, positive and negative. There is no such clear evidence within papers of the negative relationship suggested by the theoretical framework. Collin-Dufresne et al. (2001) covered this topic, assessing a negative relationship between CDS premium and risk-free rate. On the other hand, Raunig and Scheicher (2009) see that the coefficient sign is not consistent and does not take negative valued every time.

Furthermore, Hasan et al. (2015) demonstrate that the risk free is positive related in all periods and the explanatory power rises during crisis period. According to them, this link exists because higher risk-free rates translate in higher borrowing costs leading to a balance sheet worsening.

The relationship between risk free interest rate and the default probability is not so clear and the literature provides arguments in both directions, aim of this study is to provide further empirical evidence to this issue and take some conclusions out of it. As risk-free interest rate, the model applies the 10-year government bond yield provided by the European Central Bank database. Of course, many observations were applied for more than one bank, since a country can be represented by more banks.

3.4 CAMELS Variables

Due to the specific business model that differs banks from other industrial firms, topics like loan quality, liquidity position or asset/management quality beyond other things do provide incremental insight about a bank credit position. For this reason, the analysis accounts for the so-called CAMELS variables to further describe the determinants of a bank CDS spread level.

CAMELS rating system is used by regulators to assess a bank credit and overall financial condition. This system is comprised of six factors that make out the CAMELS acronym:

1. Capital Adequacy: quality and amount of capital a bank can access;
2. Asset Quality: which look deep in a bank's credit in order to identify risks;
3. Management Quality: deals with the quality of the bank oversight;
4. Earnings: assess how stable a bank's earnings are;
5. Liquidity: how quickly a bank can turn assets into cash;
6. Sensitivity to market risk: measures the sensitiveness of a bank when exposed to adverse market's developments such as a sudden change in the interest rates.

This system helps regulators to find which one is in trouble. Each variable has a rating from 1 to 5, where 1 represents the best situation possible. Then the average is taken, and banks that show an average equal or bigger than 4, are the ones that have the highest concerns and need to make immediate changes and take proper action to preserve bank's depositors.

Sometimes this average is a weighted one, where weights are under the discretion of the authority that run the tests. A common best practice consists on the following weights:

- 20% Capital adequacy and Asset quality;
- 25% Management quality;
- 15% Earnings;
- 10% Liquidity and Sensitivity to market risk.

However, the CAMEL Rating System is highly confidential, thus the judgment of the vigilant authority remains secret. Its importance was valued especially in 2008 by US authorities to recognize and decide which credit institution was more worthy of help.

This study uses the six CAMELS variables to address the topic of the credit-spread puzzle. In particular, the purpose is to analyze the incremental explanatory power they have on the CDS swap spread level beyond the structural ones.

The model picked CAMELS indicators because they provide a deeper analysis into financial institutions. In fact, this system is strictly related to banking firms, therefore it is more specific than the structural approach which is more generalized. For this reason, the analysis believes that adding those 6 variables will provide the study with more knowledge regarding credit issues. Those elements are intended to provide incremental information with respect to structural variables. Since CAMELS factors go deep into the business model of a bank, matching those two groups together will help the study to address the topic of the credit spread puzzle. It would be than interesting to assess whether it will still remain a percentage not explained by the model.

This chapter will continue analyzing each one of the indicators and state which proxy is used to converted them into proper data to run the regressions. Also, it is important to explicit the formula used for each variable in order to intuitively understand the expected relation – coefficient sign – with the dependent variable.

3.4.1 Capital Adequacy

Capital adequacy has a crucial role for the financial soundness of a bank. First, it provides the company with a caution against earnings fluctuation; in this way bank can continue to run their business even during loss periods. Second, it supports the growth of the company through their funding system and it is a valid protection instrument against insolvency of the firm's debtors.

When it comes to the banking industry, this measure has more importance since banks must meet some regulatory requirements in terms of capital assets. Holding more capital than what the law asks is indeed crucial to survive a crisis and deal with exogenous shocks as well.

The recent financial and economic crisis has led to a new analysis of the banks' regulatory framework principles; for instance, Basel III introduced new and stricter capital requirements. Particularly, banks must monitor very carefully the amount of capital hold to cover their risk weighted assets.

Basel III increased the requirements over the common equity Tier 1 and introduced more specific recommendation to the central banks. The ongoing challenges are focused on the exposure to the risk within the balance sheet, valued through the Risk Weighted Assets (RWA) – exposure weighted to their risks – measure that follows Basel guidance in the weights' computations. Risk weighted assets refers to a method to assess a banks' asset risk, which is mainly its loan portfolio.

The regulatory framework forces the bank to hold enough capital to cover unexpected losses and remain solvent under crisis circumstances. The main principle is that the amount of capital hold is related to the risk of a bank's asset. Risk weighted assets policy means that to those safer activities is given lower capital allocation, while for those riskier there is a higher risk weight. In other words, higher is the asset risk, higher will be the amount of capital reserve by the bank.

Following this regulatory framework, capital is divided into classes according to both risk and quality:

- Tier 1 is considered the capital for normal business of the firm. It is the level required to run regular bank's activities and it keeps the solvency. It is defined as the Common Tier Equity 1 ratio (CET 1).
- Tier 2 is the capital in case of the ending of one activity. It enables the entity to refund both depositors and creditors in case of the ending of an activity.

The total amount of capital a bank must hold is then equal to the 8% of the risk-weighted assets.

Tier 1 capital is made up by equity capital and disclosed reserves. This ratio – introduced by the Basel committee – allows to measure the riskiness of a bank's loan portfolio along with other assets. This method is preferred since it allows easier comparisons below banks from different countries – such as the ones within the sample size selected.

However, there are several ways through which the bank can improve their capital ratios in order to increase the overall capital adequacy. Within this topic, it should be considered the effort made to optimize the Risk Weighted Assets measure to reduce the assets absorption and keep constant the nominal balance sheet exposure.

In order to have a high capital rating, banks must comply with some best practices regarding interest and dividend rules. Furthermore, growth plan, risk control, loan and investment concentration are additional factors that contributes to a high capital adequacy rating for a bank.

The model computes the capital adequacy ratio according to the following formula:

$$Capital\ Adequacy = \frac{Tier\ 1\ Capital}{Risk\ Weighted\ Assets}$$

Following the formula above, it can be easily seen that a higher capital adequacy ratio will increase the stability of the financial institution. The relationship with the probability of default – Credit Default Swap premium –is expected to have a negative coefficient sign, since high capital adequacy ratio result in a lower probability of default and a lower CDS spread to pay for buying protection.

Both computations for Tier 1 capital and risk weighted assets are provided by the Datastream database on a quarterly basis for each bank.

3.4.2 Asset Quality

The subprime crisis witnessed in the end of 2008 had raised many doubts regarding the quality of the bank's assets. Still nowadays it represents an ongoing issue since term like non-performing loan is quite common to hear, it represents those loans that a bank has issued, and it is very unlikely to collect back because of a deterioration in the client's creditworthiness. Thus, those assets can damage the financial institution. For this reason, the CAMELS rating model takes into consideration the quality of the assets to value a credit institution.

The asset quality of a bank is mainly determined by the loans issued, since those ones represent the main assets within a bank balance sheet. Other elements affecting the asset quality can be the PPE, other off-balance sheet items or cash and equivalents. Assessing a good asset quality means to reflecting the asset level in relation with the existing risk. For this reason, an important parameter to consider is the adequacy of allowance of loan and lease losses.

It would be impossible to list all the potential sources of problematic credit position; it can be due to several mistakes by the bank that allows a borrower to be insolvent. Sometimes some well issued loans can result problematic due to unforeseen event occurred to the debtor. However, the bank management should try to protect each outstanding loan.

According to the FDIC (Federal Deposit Insurance Corporation), some errors may be due to:

- Low-quality risk assessment procedures;
- Lack of hedging position;
- Lack of supervision;
- Less focus upon changing economic conditions;
- Competition;
- Uncomplete information regarding the client's financial position.

As said before, asset quality deals with the quality of loans issued, that represents the major part of the firm's earnings. In order to assess quality, it is important to consider all risk factors that may affect the business, showing the bank's resiliency during macroeconomic downturn periods. Asset quality also arises from the efficiency of the firm's practices and investments.

In order to reflect all these concepts in one ratio, this analysis focuses mainly on the loans and the policies run to face with the intrinsic risk of this operation. For this reason, asset quality is computed according to the following formula:

$$Asset\ Quality = \frac{Provision\ for\ loan\ losses}{Total\ loan}$$

Having a high asset quality means that the bank will end up with lower loan loss provision, since the borrower has a good credit rating. Thus, the Credit Default Swap premium will be lower. For this reason, there would be expected a positive relationship between Asset quality and the dependent variable.

3.4.3 Management Quality

Assessing the quality of the management is indeed very important when it comes to value a credit institution. This factor reflects the ability of the firm to act properly during financial stress periods. In fact, a good quality management can better recognize, monitor, handle and measure the risks of a bank's activities. It encompasses the ability to run the ordinary operations safety and in compliance with the applicable regulation, both internal and external.

One of the most common elements below the firm's crisis that made an impact could be represented by the misalignment between risk and return profiles in the decisional system. The increasing necessity to reach goals – especially in terms of results in the short run – created some myopic vision below top managers. The latter undertake many investment opportunities with low attention paid to the valuation and quantification of the related risk, just to reach the settled goals in the shortest period of time possible.

The outcome could be very dangerous for the whole firm. For this reason, one of the most important aspect that is raising nowadays is the risk managing. For this reason, the ability to proper run a bank business – management quality – is indeed crucial to assess the financial soundness of a firm.

The term management – with respect to a bank – comprises both the Board of Directors (BoD), elected by the shareholders, and the executive directors besides other qualifications designated by the BoD as well. Within a complex and competitive environment such as the banking industry, it is crucial that directors are aware of their responsibilities and commit to them, in order to guarantee the stability and keep creating value for clients and shareholders.

Of course, it is not easy to put this aspect into a number to run the regression, since it is about also some subjective valuation towards some policies. But the model intends to find a good proxy for this phenomenon and – following the work of Hasan et al. (2014) – the cost efficiency ratio may be an effective measure to reflects managers' abilities. It is computed through the following formula:

$$Management\ Quality = \frac{Operating\ Revenues}{Total\ Revenues}$$

This formula aims to be a proxy for a good management. It captures the managers' ability to contain the business cost and maximize the value creation. A high level of this ratio means that the firm's businesses are run efficiently, and costs are limited.

Having a high management quality ratio will reduce the firm's default probability resulting in a lower CDS spread level. Thus, it is expected to have a negative coefficient sign for this variable.

3.4.4 Earnings

Earnings represent the bank's ability to generate income, therefore it is crucial for the ongoing operations during years. A financially sound bank is the one able to provide its shareholders with profits consistently, but also generate enough profit to sustain and increase capital in order to undertake growth opportunities.

From an authority perspective, the biggest advantage of earnings is to have the possibility to absorb future losses and increase the capital to meet current regulatory framework. Earnings are a protection against risks, they enable the bank to keep being competitive and give the resources required to strategic plans.

Analyzing a bank's earnings means to include all the operations in the profit valuation, it is important to acknowledge the core business activities and income as well. During this step is also significant to analyze whether there are some macroeconomic factors that may affects the income level, such as: new accounting principles or extraordinary event or any management action different from the normal bank functioning. Excluding those issues enables the vigilant to focus just on the basic operation of the firm that are run in a consistent way during years.

When considering earnings for a bank rating, it is important to consider a proper benchmark in which collocate those numbers, otherwise the number per se have less meaning, as said before, banking sector is a highly competitive one therefore banks should always adapt to the changing economic conditions.

Earnings stability is then crucial for the resilience of financial sector in the next future, they kept increasing from the crisis downturn experienced in the past years, even though there is no homogeneity from a worldwide perspective.

The earnings analysis requires a stepwise approach, in which the authority goes through the whole income statement. First there is the interest margin – which can be considered the core business – then the non-interest earnings and expenses, ending up with taxes as well.

In order to provide a comprehensive ratio that encompass the whole financial situation, the model uses the Return on Equity ratio to address the earning variable within the model:

$$ROE = \frac{Net\ Income}{Equity}$$

This formula is computed manually through the quarterly balance sheet provided by the Bloomberg terminal. For the reasons state above, it is expected that a high profitable firm will have lower probability of default and lower CDS spread, leading to a negative coefficient sign.

3.4.5 Liquidity

Liquidity represents the firm's financial ability to meet its obligation at expiration date. It enables the entity to handle cash flows efficiently without negatively influence daily operations, raising funds or other operations. It is indeed crucial to face the bank's balance sheet fluctuations and finance growth investment opportunities.

Funding management is then a key role within a bank, it is important to manage and analyze the liquidity in an efficient way, considering the liquidity position on an ongoing basis but also considering the possible future scenarios that may affect those levels. There are no such optimal levels of liquidity that stands for every bank, each one of them has specific liquidity levels that should meet; those ones arise from an analytical analysis upon the both current position and future possibilities a firm could undertake.

Liquidity has a cost which is a function of current market conditions and bank's risk profile. If the financing needs are not satisfied by the liquidity assets of a bank, then more funding may be asked. The management should periodically apply ad-hoc procedures to rewind the boundaries of liquidity position, for this reason it is helpful to develop some firm specific informative system to measure, control and manage liquidity risk issues.

Managing liquidity means also to value different sources of financing and its related costs. It does not mean necessarily to find the cheapest funding possible, but sometimes managers may prefer to take a more expensive one in order to avoid a financing concentration that increases the liquidity risk.

Therefore, diversifying is very important also in this field since it allows the firm to keep different financing channels which provides a more flexibility when it comes to choose one. When deciding a financing strategy, it should be considered the maturities and interest rates misalignment, a negative extraordinary event is better managed through a proper diversification within the financing sources.

Finding a ratio for the liquidity variable was intuitive. Starting from the quarterly balance sheets of the banks in the sample, the analysis extrapolates the most liquid assets (i.e. those assets which can be turned into liquidity/cash within the shortest period). For this reason, the following formula is used to proxy for bank liquidity:

$$Liquidity = \frac{Liquid\ Assets}{Total\ Assets}$$

The liquid assets category comprises cash and cash equivalents, receivable, securities bond – which are actively traded, personal liquid assets. When it comes to banking industry, most of the liquid assets are cash and equivalents and interbank activities. It is expected that a bank which holds high level of liquidity are less likely to default, for this reason the relation with the Credit Default Swap spread should be negative.

3.4.6 Sensitivity to market risk

Last element of the CAMELS indicator is the sensitivity to market risk – interest rate risk above all. It analyzes the measure through which change in interest rates, exchange rates, commodities prices may affect the revenues of a financial institution.

For the specific business model of the bank, changes in the interest rates highly affects the revenues; because of the direct impact above the loans issued as well as deposits. So, it is important to focus – from an authority perspective – upon the ability to identify, monitor and manage the market risk. Interest rates fluctuations impact earnings through the interest margin, which represents the earning from the firm's core business. It may change also the capital through the net present value calculation of future cash flow.

Hasan et al. (2014) dealt with this variable through the ratio of interest expenses to total liabilities, reflecting the exposure of the bank from a funding cost point of view. According to their theory, banks with higher cost of fund are more vulnerable, thus a positive relation should hold with the CDS spreads. Their findings confirm this positive relationship which is also statistically significant.

However, this model didn't manage to address the sensitivity variable within the model because the data availability would have led to a significant reduction of the number of observations. For statistical reasons this study is better off not represent this variable which is still explained in relation of the CDS to provide a more comprehensive view of the whole CAMELS indicators system.

This chapter has explained each variable applied in the model, it is given also an economic intuition below the expected relationship with the Credit Default Swap premium and furthermore, there are provided guidance about the proxy calculation of each variable. Table 5. Below will sum up the variables discussed in this chapter with their main features related.

Table 5. Variables description

Variable	Name	Expected Sign	Description
Structural Model variables	Leverage	+	BV Liab/(BV Liab + MV Equity)
	Volatility	+	Historical 5-years volatility
	Risk-free rate	+/-	10-year treasury bond yield
CAMELS Indicators	Capital Adequacy	-	Tier 1 Ratio
	Asset Quality	+	Loan Losses Provision Ratio
	Management Quality	-	Operating Revenues/Tot Revenues
	Earnings	-	ROE
	Liquidity	-	Liquid Assets/Tot Assets

4. Empirical Results

4.1 Descriptive Statistics

Before presenting the regression models and respective results, it would be interesting to carefully analyze the summary statistics that compose this study's dataset. Table 1 shows a representation of the main summary statistics with respect to the dependent variable, the Credit Default Swap spread, within the sample. This table is organized in order to analyze the main differences between three time periods of the sample observations. Since the sample is made up by European Banks, the reference crisis is represented by the sovereign debt one. Thus, periods are organized as following:

- Pre-crisis: 2008 – 2009.
- Crisis: 2010 – 2012.
- Post-crisis: 2013 – 2018.

Table 6. CDS spread Summary Statistics by period

CDS Spread		Time Period		
		Pre-Crisis	Crisis	Post Crisis
Statistics	Mean	129,29	212,1	119,1
	Min	45,8	51,25	18,5
	Max	335,6	830	687,5
	Std. Dev.	64,8	146,9	95

Table 6 shows the mean, minimum, maximum and standard deviation of CDS spread levels – expressed in basis points during the 3 main sub-periods within the observation timeframe.

The results for sub-periods also indicates that CDS premium follows different patterns and it is highly affected by the macroeconomic conditions under which banks operate.

From the table, the mean value of CDS spreads are highest during the crisis period according to what was expected, since turbulent periods are the one with the highest probability of default especially within the financial sector. After the crisis the mean reduced reaching lower average value than the ones witnessed pre-crisis.

Since the standard deviation measure the dispersion of data with respect to the mean of the dataset. High level of standard deviation means that spread values are distributed in an extensive range of data, which from an economic point of view may represent uncertainty. According to this interpretation, the results are consistent within time period, since the highest levels of standard deviation – uncertainty - are reported during crisis period.

Table 7 below instead represents the summary statistics regarding the whole period of observation, from 2008 to 2018; overall the number of observations is equal to 853. This table provides statistics also for the model's variables, both structural and CAMELS.

Table 7. Overall summary statistics

	Obs	Mean	Std. Dev.	Min	Max
CDS	853	146,3	116,2	18,5	830
Leverage	853	0,907	0,1281	0,4686	0,99
Volatility	853	0,3727	0,13	0,159	0,886
Rf	853	0,025	0,0159	-0,005	0,06
Cap. Adequacy	853	0,1327	0,039	0,0513	0,287
Asset Quality	853	0,0077	0,007	-0,0016	0,0548
Management Quality	853	0,186	0,4541	-5,996	2,549
Earnings	853	0,0246	0,1228	-0,882	0,2341
Liquidity	853	0,14	0,0702	0,00009	0,401

The whole average value of the CDS premium is 146,3 basis point, while the standard deviation is equal to 116,2 suggesting that presence of a wide gap between "good times" and periods of crisis. The average bank leverage levels are equal to 90,7% providing a consistency with what banks' business model suggest, which is to rely a lot upon debt financing and reach earnings through a savvy management of the interest rates' margins. The average historical 5-year volatility is equal to 37,3% while the mean of the government 10-year bond's yield is equal 2,5%.

As far as it concerns CAMELS indicators, the observations find an average of capital adequacy equal to 12,27%, provision for loan losses has a mean of 0,77% while the operating over total revenues' average is 18,6%. Finally, there is an average return on equity of 2,46% and the mean of liquid to total assets ratio is equal to 14%. It can be observed the low standard deviation with respect to some variables like the Capital Adequacy and Liquidity reflecting the role of regulators upon financial institutions; in fact banks within the model must meet some regulators' imposition regarding the Tier one capital position or holding a certain amount of liquid assets' in the balance sheets.

Amongst all the balance sheet variables, management quality – expressed as operating income over total revenue – and earnings – ROE – are the ones with highest standard deviation levels. This insight may suggest that profitability may be the balance sheet item most sensitive to the changing macroeconomic conditions.

Table 8. Correlation Matrix of the model's variables

	Leverage	Volatility	Risk-free	Capital Adeq	Asset Quality	Manag. Qual.	Earnings	Liquidity
Leverage	1.000							
Volatility	0.3733	1.000						
Risk-free	0.2242	0.0760	1.000					
Capital Adeq	-0.5472	-0.1829	-0.6308	1.000				
Asset Quality	0.3957	0.4110	0.4378	-0.4098	1.000			
Manag. Qual.	-0.2416	-0.2745	-0.1395	0.1694	-0.3966	1.000		
Earnings	-0.3262	-0.3595	-0.1923	0.2327	-0.5634	0.4239	1.000	
Liquidity	-0.0590	-0.0428	-0.5580	0.4135	-0.3741	0.0820	0.0675	1.000

The correlation matrix in Table 8 provides information regarding the correlation coefficients of both structural and CAMELS variables. The most problematic correlation findings are the ones with high values, in this case some issues within the sample emerged from the correlation of Tier1 Ratio (Capital Adequacy) and both leverage and rf; asset quality has high correlation coefficient with rf and volatility.

Moving on, management quality is positive correlated with capital adequacy and negative correlated with the provision for loan losses over total loans. Earnings are positively related with management quality and capital adequacy while a negative relation stands with risk free and asset quality. Liquidity is negatively related with leverage, volatility and asset quality and positive correlated with capital adequacy, management quality and earnings.

4.2 Methodology

The data follows different banks through time leading to a panel data model. However, some missing variables especially for 2008 forced the model to cut some banks' observations off, for this reason it can be referred to as an unbalanced set of panel data.

The study will apply a stepwise approach which is very functional for the hypothesis developed in the thesis. First, the model runs a regression just considering the CDS spreads and the structural model variables – leverage, volatility and risk-free rate. Afterwards a regression considering just the CAMELS indicator is run in order to see how the selected variables influenced the level of the 5 years senior unsecured credit default swap spread. Then, a comprehensive regression is run to understand whether the latter group of variables provide incremental information for pricing a CDS.

At the end the analysis performed should be able to answer the hypothesis question on whether the Credit Spread puzzle – in the sample – is due to just the non-exhaustive structural variables framework or it still represents an issue.

The model has the following shape:

$$Y = \alpha + \beta X + \gamma Z + \varepsilon$$

Where Y is the Credit Default Swap – expressed as a percentage –X represents the three structural variables and Y are the CAMELS indicators. The pooled linear regressions are organized in an unbalanced panel data set.

4.3 Regression with structural variables

As explained in the introduction chapter, the Merton structural model (Merton, 1974) defines a direct relationship between pricing of credit instrument – such as a Credit Default Swap contract – and the economic determinants for the default probability – financial leverage, volatility and risk-free interest rate. In the second chapter where the model is descripted, each variable is analyzed separately and it is provided an economic intuition below the expected sign of the coefficient, which represents how the variable relates with the dependent one.

Table 9. below report the results for the regression with the structural variables only. The regressions are run by the statistical software Stata according to the following formula:

$$CDS = \alpha + \beta_1 * \text{ Leverage} + \beta_2 * \text{ Volatility} + \beta_3 * \text{ Risk-free}$$

All the coefficients estimated in the regression are significant from a statistical point of view. As a matter of fact, the t-statistics are provided in parenthesis below the coefficient number, in order to be statistically significant, it should give values above +2 and below -2 according to the best practices.

As far as it concerns the coefficients, they assume the following values:

- Leverage: this coefficient is equal to 0.0056 (t = 2.17) which is consistent with the assumption made. In fact, the coefficient sign is positive meaning that the highest is the debt level of a firm highest will be its probability to go default, thus the CDS spread increase. The low level of the coefficient may be due to the sample size applied within the model. The statistical significance suggests that leverage is useful to determine credit risk not only for industrial firms but also financial ones, even if the latter have a narrower leverage distribution than the former due to business specific needs.
- Volatility: the respective coefficient is equal to 0.026 (t = 10.67), consistent with what predicted by the structural model. This variable is computed from the historic 5-years share price volatility and it is used

to proxy for a firm's asset volatility. High level of this value represents a high probability for the asset to fall below the default threshold, for this reason the default likelihood increases and so the Credit Default Swap premium as well.

- Rf: this variable is the most controversial one within the Merton structural model framework, since it is not clear its link with the default probability. The model developed presents a positive coefficient equal to 0.387 (t = 20.03), providing more empirical arguments to that part of the literature that assumes a positive relationship with the default likelihood. This latter interpretation may lie on the fact that high interest rates increase the banks' borrowing costs affecting their interest rates margin.

Below it is provided the Stata table for the regression's results. Furthermore, the software automatically tests the null hypothesis according to which the coefficient's vector is all equal to 0. In this case the null is rejected (i.e. Prob > 0).

Table 9. Regression with Structural variables

	Coefficient
Leverage	.0056** (2.17)
Volatility	.0265*** (10.67)
Risk-free	.3877*** (20.03)
Constant	-.01007*** -4.67

Number of obs	853
F (3, 849)	213.09
Prob > F	0.0000
R-squared	0.4295
Adj R-squared	0.4275

Table 9. presents the regression results for the structural variables only. The superscripts ***, **, * indicate significance at 1%, 5%, 10% respectively

Another important variable to consider is the R-squared, in this case it is equal to 42,95%. This means that the structural predictors account for the 42,95% of the CDS premium variation. This number is in line with the ones provided by other papers that address the determinants of the credit spread issues through structural variables. Stata provides the Adjusted R-squares as well, which is an adjustment made for the number of predictors and sample size, the purpose is to avoid that the model overfits data. In this case it is equal to 42,75%, so there is not a big difference with the previous measure.

The R-squared finding supports the credit-spread puzzle theory developed in the early hypothesis; as a matter of fact – within the model's sample size – those variables can explain only a limited percentage (42,95%) of the credit default swap's spread variation. This is consistent with the credit spread puzzle literature according to which the structural model variables fail to predict the whole change in the credit spread, in this case represented by the Credit Default Swap premium. Given this finding, it would be useful to further investigate this issue and try to understand whether the credit spread puzzle in my sample is still an issue after having added more firm specific variables – CAMELS indicators.

Here the intercept has a negative value equal to – 0.01. Statistically this means that the y takes this value when all the explanatory variables are equal to 0. From an economic perspective, this element should not have a relative valuable meaning since the likelihood that all the variables are 0 is very low.

4.4 Regression with CAMELS indicators

Next, the thesis investigates whether CAMELS rating indicators can influence levels of CDS spreads. Therefore, a linear pooled regression is run with capital adequacy, asset quality, management quality, earnings and liquidity as regressor. The regression takes the following shape:

$$CDS = \alpha + \beta_1 \text{*Cap.Adeq.} + \beta_2 \text{*AssetQuality} + \beta_3 \text{*Man.Quality} + \beta_4 \text{*Earnings} + \beta_5 \text{*Liquidity}$$

Chapter two of this work provides insight about each one of the variables with the relative proxies used for the calculation; it is also state what should be the coefficient sign to determine the kind of relationship with the dependent variable.

The coefficients found have the following values:

- Capital adequacy: this coefficient is equal to - 0.338 (t = - 3.47). According to the t-statistics this variable is significant from a statistical point of view. From an economic perspective, it should be considered that this variable is proxied by the Tier 1 ratio. Therefore, high level of Tier 1 capital – composed by common stocks and disclosed reserves or retained earnings – should lower the probability of default. So, this negative coefficient is indeed in line with the expectations and what credit theory suggests.
- Asset quality: the relative β of this variable is equal to 0.189 (t = 3.02), statistically significant. It is significant also from an economic point of view. In fact, it was expected a positive relationship between the ratio of provision for loan losses over total loan and it is found a positive regressor coefficient that supports the underlying theory. Also, the magnitude of this relation is very high compared to the other variables.
- Management quality: it has a coefficient of – 0.0005 which reflects a very low impact upon the CDS spread variable. Since the t-stat is equal to – 0.69 there is not a statically significant relationship for this variable. However, the sign of the coefficient suggests a negative relationship between the ratio of Operating Revenues to Total Revenues, which was in line with the expectations stated in chapter 2.

- Earnings (Return on Equity): this regressor coefficient is equal to – 0.027 and it is statistically significant (t = - 7.90). It was expected a negative relationship, since high level of return on equity will decrease the banks' default likelihood.
- Liquidity: this value is proxied by the liquid assets over total assets ratio. High levels of liquidity should increase the bank's financial stability and, so, decrease the credit default swap premium. Indeed, the coefficient found has negative values, - 0.036 consistent with the assumptions made. Also, the variable is statistically significant (t = - 6.68).

Table 10. Regression with CAMELS indicators

	Coefficient
Cap. Adequacy	-.03389*** (-3.47)
Asset Quality	.1891*** (3.02)
Manag. Quality	-.00057 (-0.69)
Earnings	-.02765*** (-7.90)
Liquidity	-.03697*** (-6.68)
Constant	.0239*** (14.78)

Number of obs	853
F (5, 847)	69.54
Prob > F	0.0000
R-squared	0.2910
Adj R-squared	0.2869

Table 10. presents the regression results for the CAMELS variables only. The superscripts ***, **, * indicate significance at 1%, 5%, 10% respectively

To sum up the main conclusions for this second regression, it can be seen that – apart from the Management quality variable – all the others are statistically significant and well fit the model. They do account to determine the credit default swap premium, and the relationship of each variable with the dependent one is consistent with the economic interpretation of default likelihood. Above all, the asset quality variable is the one with the highest magnitude that affects more than others the level of CDS ($\beta = 0.189$).

The adjusted R-squared for this second model is equal to 28.69%, below the explanatory power of the structural model regressors but still important from a statistical perspective. Furthermore, this value is in line with the current literature findings with respect to the CAMELS indicators system (Hasan et al. 2014).

Also, in this second regression, Stata software rejects the null hypothesis according to which the variables' coefficients vector is equal to 0 meaning that there is no relationship between the variables and the explanatory ones chosen.

4.5 Regression with both structural and CAMELS indicators

Purpose of this thesis is to address the credit spread puzzle issue, trying to provide empirical evidence to the literature with more findings regarding the presence, or not, of the puzzle. By running a third regression where both the structural and CAMELS variable groups are considered the analysis aims to answer the following two questions:

1. Do the CAMELS indicators provide incremental evidence than the structural variables regarding a banks' financial position?
2. Is the credit spread puzzle – in my sample – due to just the non-exhaustive explanatory power of the structural variables?

In order to address these topics, it is run a linear pooled regression with all variables in it. The focus will be the R-squared measure that will enable this study to end up with some conclusions.

The formula of this third regression will then be:

$$Y = \alpha + \beta X + \gamma Z$$

Y: CDS spread levels

X: Structural model variables (Leverage, volatility and Risk-free)

Z: CAMELS indicators (Capital adequacy, Asset quality, Management quality, Earnings, Liquidity)

Therefore, Table 11 below provides results for the final regression that includes all variables. The only non-significant variable from a statistical perspective remains the management quality, which in this study is not a factor affecting the CDS spread differently from the findings of Hasan et al. (2014). It emerges also the changing coefficients' sign for capital adequacy and asset quality, this is due to some "interferences" made when regressing with the structural variables as well.

Table 8 provides the correlation matrix coefficients where it can be seen the high correlation these two variables have with the structural ones (- 0.63 is the coefficient between capital adequacy and the risk-free interest rate and 0.4378 the correlation between risk free and asset quality). This situation has influenced the coefficient sign. However, also this regression is statistically significant, and the null hypothesis is rejected.

Table 11. Regression with both structural and CAMELS variable

	Coefficient
Leverage	.0121*** (4.13)
Volatility	.0216*** (8.57)
Risk-free	.43623*** (16.75)
Cap. Adequacy	.06833*** (6.20)
Asset Quality	-.11283** (-2.01)
Manag. Quality	-.00008* (-0.11)
Earnings	-.0239*** (-8.04)
Liquidity	-.01517*** (-2.96)
Constant	-.0206*** (-5.38)

Number of obs	853
F (8, 844)	104.24
Prob > F	0.0000
R-squared	0.4970
Adj R-squared	0.4922

Table 11. presents the regression results for both structural and CAMELS variables. The superscripts ***, **, * indicate significance at 1%, 5%, 10% respectively

As said at the beginning of this paragraph, the most interesting measure showed in this regression is the explanatory power. R-squared adjusted is equal to 49,22%, which is 7 percentage points higher than the model explained by the structural Merton one. This finding means that including both structural and CAMELS variables improves the model fit from 42,75% to 49,22% consistent with the hypothesis developed in this study, suggesting that CAMELS indicators hold complementary information regarding a bank credit risk, to respond to the research question number one.

To answer research question number two, the R-squared level is still far from the 100% indicating that the credit spread puzzle – in the model – still represents an issue. In other words, there is a robust part of the bank credit risk that is not explained by both structural and CAMELS variable.

4.6 Impact of crisis

In this section the analysis aims to investigate the impact of the crisis upon structural model's variables, particularly volatility and leverage. Since the sample consists of European Banks, the crisis accounted for is the sovereign debt one witnessed in the period 2010 – 2012.

It is then added a dummy variable to account for crisis periods which takes value 1 for those observation that fall within the crisis timeframe otherwise the variable takes value 0. Afterwards new variables are created through the interaction of the original variables and the dummy one. The new regression takes the following shape:

$$CDS = \alpha * Leverage + \beta * (leverage * dummy\text{-}crisis) + \ldots$$

This process is of course repeated for the volatility variable as well. The main interest thing to see here is the impact of those variables during crisis period.

From the model specification, the coefficients should be read in the following way:

- α represents the leverage effect under non-crisis periods, since in this period β is going to be equal to 0;
- $(\alpha+\beta)$ will then reflect the effect during crisis periods.

Table 12. Regression with Dummy variable

	Coefficient
Leverage	.00266* (1.01)
Volatility	.03147*** (11.02)
Risk-free	.34707*** (16.39)
LeverageCrisi	.01374*** (5.28)
VolatilityCrisis	-.02514*** (-4.41)
Constant	-.00888*** (-4.17)

Number of obs	853
F (5, 847)	138.75
Prob > F	0.0000
R-squared	0.4503
Adj R-squared	0.4470

Table 12. presents the regression results when the crisis is accounted for. The superscripts ***, **, * indicate significance at 1%, 5%, 10% respectively

Risk-free variable was not considered in conjunction with the dummy, since it is still not clear what should be the relationship with the credit default swap. Regarding the other two structural variables, they are both statistically significant. Leverage crisis' coefficient is higher than non-crisis periods, it is indeed equal to 0.016 (t = 5.28). This finding suggests that the negative impact of leverage is stronger during crisis period than non-crisis. On the other hand, the volatility variable under crisis is 0.0063 (t = - 4.41), lower than the non-crisis period within the sample size and the model design.

5. Conclusions

This study analyzes the determinant of the Credit Default Swap levels on a sample of 20 listed European banks, through quarterly observations that comprise a time period from 2008 – 2018. The financial institution's credit risk models are not examined enough by the current literature because of several reasons: the specific business model and the robust impact of bank regulators above all.

However, banking industry does have a prominent role in the economic landscape especially after the financial crisis experienced in 2008; for this reason, it is crucial to perform some more work upon this sector from a credit risk point of view as well. Thus, CDS – which are a measure of a banks' default risk – deserve more labors from the outstanding credit literature.

Through an unbalanced panel data sample constituted by 853 observations, the work aims to understand the determinants of European banks' CDS. First, it contributes to the literature by providing additional empirical evidences regarding the applicability of the structural model variable to price banks' CDS spread. This evidence is taken from a pooled linear regression in which the dependent variable – CDS spread – regresses with the Merton structural model's ones – leverage, asset volatility and risk-free rate. The results suggest that all of them are economically and statistically significant, but still there is a percentage of the spread's variation that is not explained by those variables, consistent with the credit-spread puzzle theory.

So, the model adds another group of variables represented by CAMELS indicators. This group is made up of 6 firm-specific variables (capital adequacy, asset quality, management quality, earnings, liquidity and sensitivity to market risk). Those indicators are commonly used by authorities to assess a bank's financial position through an ad-hoc credit rating measure. Running the regression with only the six CAMELS variables suggests that – except for the management quality – all of them are both statistically and economically significant.

Afterwards, it is run a regression with both structural and CAMELS indicators, and the explanatory power, measured by the adjusted R-squared, improved. This finding suggests that the CAMELS indicators hold incremental information beyond the structural variables, which are the commonly used ones by practitioners to deal with credit spread.

However, there is a part of the model not explained by the variable picked, thus the credit spread puzzle is still an issue even after having 6 more variables added to the structural ones. In this sense, the thesis provides the literature with more empirical evidence upon this topic which in the future should be addressed with more focus and effort since it is not something just related to the structural variables as this work suggests.

Additionally, the study addresses the topic of the crisis by adding a dummy variable within the model. This variable interacts with both leverage and volatility. Findings are both economically and statistically significant suggesting that the negative effect of the leverage upon the CDS spread tents to be stronger during crisis period, while for volatility is the opposite.

To conclude, this study helps the current literature through its findings regarding credit risk topics which are more focused upon industrial companies than financial institutions. Furthermore, it provides the authorities with a new instrument – the Credit Default Swap – when monitoring the banking industry's stability. Those spreads can be used as warning alert tools that triggers the banks' supervisors to change their decisions according to the different alerts from the CDS market.

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Department of Corporate Finance

Course of Asset Pricing

Determinants of CDS spreads

Empirical Analysis over European Banks

- SUMMARY -

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ACCADEMIC YEAR

2018/2019

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1. Introduction

After the recent financial crisis, the attitude towards banks has changed: many efforts were put to the direction of any warning system that could help prevent or avoid other negative shocks to happen again. One indicator is the Credit Default Swap (referred to as CDS from now on) spreads, which reflects a firm's default likelihood. It is a derivative contract where the "protection buyer" periodically pays an amount – spread – to the "protection seller" who repays the counterparty losses when a credit event occurs. Therefore, CDS contract spread levels provide insight regarding a firm financial soundness position. Many researchers have focused their attention upon the CDS of industrial companies. However, it is interesting to analyze the banking industry given the systematic importance of these entities and their role during the financial crisis. For these reasons, this thesis aims to provide some empirical evidence of what are the CDS spread determinants upon European Banks using pooled linear regression models.

The study addresses the topic of the credit spread puzzle according to which the structural variables – developed within Merton model– fail to explain the whole variability of the credit-spread. To do that, the analysis runs different regressions applying a stepwise approach. First, it is run a regression with just the three structural variables as the independent regressors. It is found that each variable is statistically and economically significant for the CDS of the banks in the sample. The coefficient values are robust to model specification. The adjusted R-squared is 42,75% indicating that the structural variables explain just a portion of the credit-spread variance consistent with what the credit-spread puzzle theory suggests. Afterwards, further variables are added into the model to examine whether they provide additional information and if the credit-spread puzzle, in the sample, is still an issue. Those variables are the so-called CAMELS which is an acronym for the 6 variables that carries-out: capital adequacy, asset quality, management quality, earnings, liquidity and sensitivity to market risk. The regression with just CAMELS indicators shows that, except for management quality, all the variables are statistically and economically significant. The coefficient signs define the relationship with the dependent variable and each one of them is in line with the expectations.

It is then run another regression with both groups of variables, showing that those are significant from a statistical point of view, except for management quality. The most interesting feature here is the adjusted R-squared, equal to 49,22%. Thus, the inclusion of CAMELS variables improves the model fit of 7 percentage points suggesting that they do provide complementary information with respect to the Merton model variables. However, there is still a robust percentage of variation in the dependent variable that is not explained, thus the credit-spread puzzle remains an issue within the sample considered. It is also examined the impact of the sovereign debt crisis over two indicators (leverage and volatility) by adding a dummy variable. It is found that leverage has a stronger negative impact during crisis than non-crisis period while for volatility is valid the opposite.

This study will then contribute to the literature by providing empirical evidence to the applicability of structural variables for pricing banks' CDS spread while the contribution upon credit risk mainly focuses on industrial companies. It also provides the authorities with a new warning system, CDS spread, that can be useful during monitoring activities upon the banking industry's stability.

2. Overview of Credit Default Swap

Credit risk is one of the most important topics among the whole finance literature due to the direct connection with the financial soundness of the world banking systems. CDS contract represents a controversial security among the derivatives market. For this reason, both institutions and regulators are seeking for the right way to measure and manage this risk. Within a CDS contract, an entity purchases insurance against a predefined credit event in change of a fixed periodical income. On the other side, the "protection seller" collects periodically an income and commits to pay a certain amount when a credit event occurs. CDS contracts could be viewed as an insurance against the default of the underlying entity. The credit event represents the instance that triggers the payments from the protection seller. The failure of an entity to meet its obligation towards the reference firm is defined as credit event, others are the delay in payments, debt restructuring, non-execution of one obligation, moratorium or downgrading.

An important aspect of the CDS contract is its spread which is quoted in basis point of a certain notional amount. For such reasons, this spread is an indicator of the underlying entities' credit risk. The thesis aims to analyze what determines the level of the CDS spread with respect to European Banks.

2.1 CDS market

Credit Default Swap contracts are traded in the OTC market; institutional and legal guidance are given by ISDA (International Swaps and Derivatives Association). The ISDA role was indeed crucial for the development of the credit derivative market, since it had provided a standardize contract in 1992 that enabled OTC market participants to have a fully documented, but flexible at the same time, contract to start the negotiations with. Thus, there was an increase in the incentive to settle for these contracts.

CDS contracts had a crucial role in the credit crisis highlighting the need to increase both transparency and regulation. After a sharp increase in the period prior the financial crisis, CDS market started to shrink very fast. Besides the notional amount, another massive reduction concerned the inter-dealer position, thanks to the CCP netting activity upon symmetric positions. Overall, both CCP and the standardization process had helped to reduce credit and counterparty risk.

2.2 CDS and the financial crisis

CDS contracts are commonly associated with the recent financial crisis. A prominent role in that period was played for sure by the banking sector, one of its major players was in fact the investment banking Lehman Brothers Inc. However, the financial crisis is such a highly complex issue that it is a mistake to consider CDS the main cause of what had happened. One negative outcome can be the fact that this derivative may have aggravate the crisis' negative effects, but this must be proven anyway. What is indeed very interesting to see is that recent studies affirm the CDS contracts to be a very powerful indicator of a bank financial soundness. Since the bank's CDS spread level has reached their highest levels immediately before their failure, markets participants recognize them as a reliable riskiness indicator. The mechanism is quite straight forward: higher is the probability of a credit event to occur, higher will be the spread quotation. For this reason, regulator and market participants must pay more attention to the behavior of a bank CDS spread. It is important to leave this market free to act since some restriction may reduce drastically their quality to be good solvency predictors, yet it is still crucial to increase the transparency and the disclosures.

2.3 Credit Risk models

When it comes to pricing a credit default swap contract (i.e. defining its premium), the existing literature deals with two main models: structural model and reduced-form model.

2.3.1 Structural model

The biggest intuition below Merton model is to see the firm's equity as a call option on its assets. The equity value is then calculated through the Black-Scholes-Merton option-pricing model, intended to be a call option where the underlying is the firm's assets and the strike price is the face value of the debt. Default happens when the call option is out-of-money (i.e. the firm's asset value is lower than the face value of the debt). For this reason, it is very important to consider some firms fundamentals such as leverage and asset volatility.

This model depends on asset volatility, while the equity value is often observed in the market. The usual approach is used to estimate the assets' value and volatility σ through the Black-Scholes call-option formula. E_t= BSCall (A_T , K, r, T, σ) where K and T are defined by the firms' debt structure.

2.3.2 Reduced-Form model

The reduced-form model builds different assumption from the structural one. First, the ZCB debt can be traded. Rf is stochastic meaning that it can change and take different values considering in this way the interest rate risk. Furthermore, default can occur anytime. The state of the economy, which describes the model, is made up by different vectors of macroeconomic variables (GDP, employment etc.). The probability of default is driven by macroeconomic variables, but default is an idiosyncratic event. Nowadays many practitioners use the reduced form more than the structural one since it lies upon more realistic assumptions. This comparison may have highlighted some important limits of the Merton's structural model which can be considered the starting point for what this thesis refers to as the credit-spread puzzle.

2.4 Credit Spread Puzzle

There are some findings according to which, after matching historical default, recovery rates and equity premium, the structural model variables fail to predict the actual credit spread, due to the so called "credit spread puzzle". J. Amato and E. Remolona (2003) state that the origins below the credit spread puzzle might be the difficulty to fully diversify a corporate bond portfolio; hence the huge spread is due to an undiversified credit risk price that lead to a higher bond yield.

The structure of this analysis aims to address the topic of the credit-spread puzzle. The model starts to explain levels of the European Banks CDS spread by applying the structural model variables, it will be interesting to see the explanatory power of those structural model variables (leverage, asset volatility and risk-free rate). Afterwards, the model adds further factors that may provide more evidence to the CDS premium levels – CAMELS. After having noticed whether those indicators have incremental explanatory power, the model aims to understand if credit spread puzzle represents still an issue.

3. Research design

The regression model applies a stepwise approach to see how the explanatory power is influenced by adding some CAMELS indicators to the normal structural framework. Those first regressions will provide some insights about the determinants of the CDS spread level. An important measure used to interpret the results is the R-squared. In accordance to the current studies and the credit spread puzzle framework, it is expected that the R-squared from the first regression does not explain the whole dependent variable. By adding CAMELS indicators to the regression, the analysis aims to highlight the increase in the R-squared value.

Furthermore, the model wants to investigate the resultant coefficient in the regressions, to see whether those selected variables are statistically and economically significant. The regressions are performed through a specific statistic software called STATA, which automatically runs a hypothesis test in which the null hypothesis is that the vector coefficient is equal to zero. To see whether each variable has a statistical significance, it is utilized the t-stat for each variable, which should be higher than +2 and lower than -2.

3.1 Data

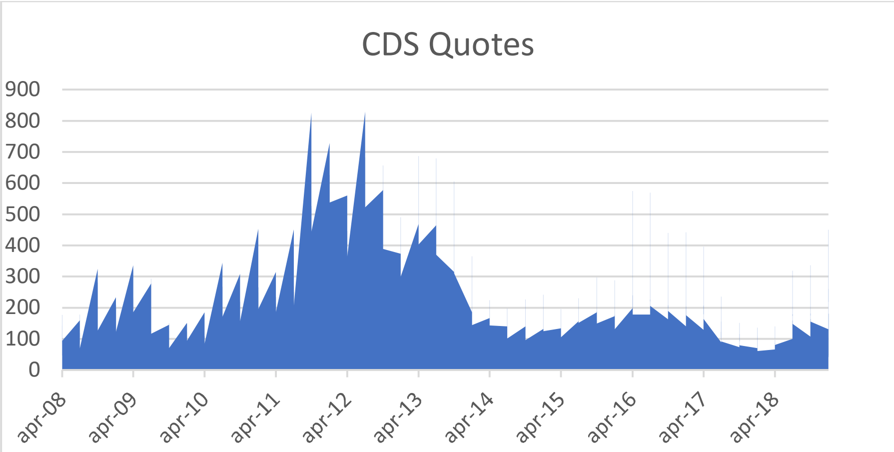
The sample consists of 20 Listed European Banks from the first quarter of 2008 to the end of 2018. Overall it is made up by an unbalanced panel data set of 853 observations. The sample is divided as following: Belgium (1), France (3), Germany (1), Great Britain (2), Italy (5), Spain (3), Sweden (3), Switzerland (2).

3.2 Dependent Variable

The model considers the senior unsecured 5-years maturity Credit Default Swap Spread contract to be the dependent variable. Meaning that the CDS contracts selected have the underlying assets represented by a 5-years maturity senior unsecured bond issued by the respective bank. It is picked the unsecured one because it is the most common one, thus it helped the data to cover the whole sample size.

CDS contracts maturities are flexible. However, the 5-year maturity contract is the most liquid one and it represents slightly the 85% of the whole CDS market. CDS quotes are collected directly from the Bloomberg terminal. Furthermore, it is important to highlight that the frequency chosen for the CDS quotes is consistent and compatible with the accounting data availability, that have the same calendar date, and represents an important aspect of the CAMELS variables constitution. In this sense, there is time consistency between the data selected.

Graph 1. Distribution of the CDS spread



Graph 1 shows a chart of the CDS quotes – expressed in basis point - that constitutes the model's sample. The crisis hit the Europe financial system through the well-known sovereign debt crisis. The beginning of the Eurozone crisis is intended to be 2010. This is supported by the massive increase that the chart shows since 2010. The post-crisis period goes from 2013 to 2018 witnessed an improvement of the economic system; during this period, chart shows a decline in the CDS premia reflecting a better financial position of the overall bank system.

3.3 Explanatory Variables

Empirically what is shown is that the Merton's structural variables have weak explanatory power alone. Thus, many studies, like this one, argue that by adding more variables it is possible to increase the explanatory power of the model providing further evidence to the CDS spread levels beyond the structural framework. To address this issue, the model's structure provides two groups of explanatory variables – structural and CAMELS - and it applies a stepwise approach to run its regressions.

3.3.1 Leverage

This measure is strictly sector-specific; thus, it is important to considered also the banking sector landscape when it comes to leverage. Banks have different asset and liability structure since they rely mainly on deposits to finance their activities. For this reason, their leverage ratio tents to be higher than the corporate industrial sector. Differently for many studies that apply balance-sheet ratio (Chiaramonte and Casu, 2013) or those that apply the equity stock return as a proxy (Annaert et al., 2013), this study applies the formula provided by Hasan, Liu and Zhang (2014) to account for this variable: $Leverage\ = \frac{BV\ Liabilities}{(BV\ Liabilities + MV\ Equity)}$. With this formula, a high value of leverage reflects high level of debt, thus higher CDS premium, consequently a positive relation should stand. All the book value numbers are calculated through the quarterly results provided by the Bloomberg terminal. While market value of Equity is instead taken from the Datastream Thomson Reuters.

3.3.2 Volatility

According to the structural Merton model (1974), another important determinant of the Credit Default Swap spread is the firm's asset volatility, which is very difficult to observe indeed. For this reason, it is crucial to find an available measure to proxy this important variable; the most common one is the equity volatility which is applied in this model as well. An increase in equity volatility results in a rise in the asset's value volatility; the latter one will then increase the probability of the asset level to hit the default threshold, expressed as a function of the current outstanding debt. It is expected a positive relationship between equity volatility and CDS spread. Equity volatility measures are taken form the Thomson Reuters Datastream which provided, on a quarterly basis, the 5 years historic volatility.

3.3.3 Risk-free interest rate

According to the Merton's framework, risk-free rate represents the risk-adjusted drift of the firm value. Thus, it is intended to be negatively related to the CDS spread. As a matter of fact, interest rates are positively related to the economic growth and negatively to default probability. However, current literature represents both type of connection, positive and negative. An increase in interest rates may lead to higher cost of funding for instance. So, the relationship between risk free interest rate and the default probability is not so clear and the literature provides arguments in both directions, aim of this study is to provide further empirical evidence to this issue and take some conclusions out of it. As risk-free interest rate, the model applies the 10-year government bond yield provided by the European Central Bank database.

3.4 CAMELS Variables

Due to the specific business model that differs banks from other industrial firms, topics like loan quality, liquidity position or asset/management quality beyond other things do provide incremental insight about a bank credit position. The model picked the CAMELS indicators because they provide a deeper analysis into financial institutions. In fact, this system is strictly related to banking firms, therefore it is more specific than the structural approach. For this reason, the model accounts for the so-called CAMELS variables to further describe the determinants of a bank CDS spread level. This system helps regulators to find which one is in trouble and more worthy of help.

3.4.1 Capital Adequacy

Capital adequacy has a crucial role for a bank's financial soundness. It provides the company with a caution against earnings fluctuation; in this way bank can continue to run their business even during loss periods.

Moreover, it supports the growth of the company through their funding system and it is a valid protection instrument against insolvency of the firm's debtors. The regulatory framework forces the bank to hold enough capital to cover unexpected losses and remain solvent under crisis circumstances. The main principle is that the amount of capital hold is related to the risk of a bank's asset. The model computes the capital adequacy ratio according to the following formula: $Capital\ Adequacy = \frac{Tier\ 1\ Capital}{Risk\ Weighted\ Assets}$. Following this formula, a higher capital adequacy ratio will increase the bank's stability, thus it is expected a negative coefficient sign.

3.4.2 Asset Quality

The asset quality of a bank is mainly determined by the loans issued, since those ones represent the main assets within a bank balance sheet. Other elements affecting the asset quality can be the PPE, other off-balance sheet items or cash and equivalents. Assessing a good asset quality means reflecting the asset level in relation with the existing risk. An important parameter to consider is then the adequacy of allowance of loan and lease losses. Asset quality is computed according to the following formula: $Asset\ Quality = \frac{Provision\ for\ loan\ losses}{Total\ loan}$ Having a high asset quality means that the bank will end up with lower loan loss provision, since the borrower has a good credit rating. Thus, the CDS premium will be lower expecting a positive relationship between Asset quality and the dependent variable.

3.4.3 Management Quality

This factor reflects the ability of the firm to act properly during financial stress periods. A good quality management can better recognize, monitor, handle and measure the risks of a bank's activities. It encompasses the ability to run the ordinary operations safety and in compliance with the applicable regulation. It is not easy to put this aspect into a number to run the regression, since it is about also some subjective valuation towards some policies. Yet the model aims to find a good proxy for this phenomenon and – following the study of Hasan et al. (2014) – the cost efficiency ratio may be an effective measure to reflects managers' abilities. It is computed through the following formula: $Management\ Quality = \frac{Operating\ Revenues}{Total\ Revenues}$. This formula is a proxy for good management capturing managers' ability to contain the business costs and maximize the value creation. It is expected to have a negative coefficient sign for this variable.

3.4.4 Earnings

Earnings represent the bank's ability to generate income, therefore it is crucial for the ongoing operations during years. A financially sound bank is the one able to provide its shareholders with profits consistently, but also generate enough profit to sustain and increase capital in order to undertake growth opportunities. This thesis uses the Return on Equity ratio to address the earning variable within the model: $ROE = \frac{Net\ Income}{Equity}$. The formula is a comprehensive measure of a bank's profitability, it is computed manually through the quarterly balance sheet provided by the Bloomberg terminal. For the reasons stated above, it is expected a negative coefficient sign.

3.4.5 Liquidity

Liquidity represents the firm's financial ability to meet its obligation at expiration date. It enables the entity to handle cash flows efficiently without negatively influence daily operations, raising funds or other operations. It is indeed crucial to face the bank's balance sheet fluctuations and finance growth investment opportunities. Finding a ratio for the liquidity variable was intuitive. Starting from the quarterly balance sheets of the banks in the sample, the model extrapolates the most liquid assets. For this reason, the following formula is used: $Liquidity = \frac{Liquid\ Assets}{Total\ Assets}$. It is expected that a bank which holds high level of liquidity are less likely to default, for this reason the relation with the Credit Default Swap spread should be negative.

3.4.6 Sensitivity to market risk

Last element of the CAMELS indicator is the sensitivity to market risk, interest rate risk above all. It analyzes the measure through which change in interest rates, exchange rates, commodities prices may affect the revenues of a financial institution. For the specific bank business model, changes in the interest rates highly affects the revenues. However, this thesis didn't manage to address the sensitivity variable within the model because the data availability would have led to a significant reduction of the number of observations. For statistical reasons this study is better off not represent this variable. However, it is still explained in relation of the CDS to provide a more comprehensive view of the whole CAMELS indicators system.

4. Empirical Results

4.1 Descriptive Statistics

Before presenting the regression models and respective results, it would be interesting to carefully analyze the summary statistics that compose this study's dataset. Table 1 shows a representation of the main summary statistics with respect to the dependent variable, the Credit Default Swap spread, within the sample.

Table 1. CDS spread Summary Statistics by period

CDS Spread		Time Period		
		Pre-Crisis	Crisis	Post Crisis
Statistics	Mean	129,29	212,1	119,1
	Min	45,8	51,25	18,5
	Max	335,6	830	687,5
	Std. Dev.	64,8	146,9	95

The results for sub-periods also indicates that CDS premium follows different patterns and it is highly affected by the macroeconomic conditions under which banks operate. From the table, the mean value of CDS spreads are highest during the crisis period according to what was expected. After the crisis the mean reduced reaching lower average value than the ones witnessed pre-crisis.

4.2 Methodology

The data follows different banks through time leading to a panel data model. However, some missing variables especially for 2008 forced the model to cut some banks' observations off, for this reason it can be referred to as an unbalanced set of panel data. The study will apply a stepwise approach which is very functional for the hypothesis developed in the model. The latter has the following shape: Y = α + βX + γZ + ε. Where Y is the Credit Default Swap, X represents the three structural variables and Y are the CAMELS indicators. The pooled linear regressions are organized in an unbalanced panel data set.

4.3 Regression with structural variables

The regressions are run by the statistical software Stata according to the following formula:

$$CDS = \alpha + \beta_1 * \text{Leverage} + \beta_2 * \text{Volatility} + \beta_3 * \text{Risk-free}$$

All the coefficients estimated in the regression are significant from a statistical point of view. As far as it concerns the coefficients, they assume the following values:

- Leverage: this coefficient is equal to 0.0056 (t = 2.17) which is consistent with the assumption made. In fact, the coefficient sign is positive meaning that the higher is the debt level, higher will be its probability to go default. Low level of the coefficient may be due to the sample size applied within the model.
- Volatility: the respective coefficient is equal to 0.026 (t = 10.67), consistent with what predicted by the structural model.
- Rf: this variable is the most controversial one within the Merton structural model framework. The model developed presents a positive coefficient equal to 0.387 (t = 20.03), providing more empirical arguments to that part of the literature that assumes a positive relationship with the default likelihood.

Table 2. Regression with Structural variables

	Coefficient
Leverage	.0056** (2.17)
Volatility	.0265*** (10.67)
Risk-free	.3877*** (20.03)
Constant	-.01007*** (-4.67)

Number of obs.	853
F (3, 849)	213.09
Prob > F	0.0000
R-squared	0.4295
Adj R-squared	0.4275

Table 2. presents the regression results for the structural variables only. The superscripts ***, **, * indicate significance at 1%, 5%, 10% respectively.

Another important variable to consider is the adjusted R-squared, in this case it is equal to 42,75%. This means that the structural predictors account for the 42,75% of the CDS premium variation. The R-squared finding supports the credit-spread puzzle theory developed in the early hypothesis. Given this finding, it would be useful to further investigate this issue and try to understand whether the credit spread puzzle in my sample is still an issue.

4.4 Regression with CAMELS indicators

The regression takes the following shape and values:

$$CDS = \alpha + \beta_1 *Cap.Adeq. + \beta_2 *AssetQuality + \beta_3 *Man.Quality + \beta_4 *Earnings + \beta_5 *Liquidity$$

- Capital adequacy: this coefficient is equal to - 0.3389 (t = - 3.47). According to the t-statistics, this variable is significant from a statistical point of view. From an economic perspective, high level of Tier 1 capital should lower the probability of default. So, this negative coefficient is indeed in line with the expectations and what credit theory suggests.
- Asset quality: the relative β is equal to 0.1891 (t = 3.02), statistically significant. It is significant also from an economic point of view. Moreover, the magnitude of this relation is very high compared to the other variables.
- Management quality: it has a coefficient of – 0.0005 which reflects a very low impact upon the CDS spread variable. Since the t-stat is equal to – 0.69 there is not a statically significant relationship for this variable. However, the sign is in line with what suggested by the theory.
- Earnings (Return on Equity): this regressor coefficient is equal to – 0.027 and it is statistically significant (t = - 7.90). It was expected a negative relationship.
- Liquidity: the coefficient found has negative values, - 0.036 consistent with the assumptions made. Also, the variable is statistically significant (t = - 6.68).

Table 3. Regression with CAMELS indicators

	Coefficient
Cap. Adequacy	-.03389*** (-3.47)
Asset Quality	.1891*** (3.02)
Manag. Quality	-.00057 (-0.69)
Earnings	-.02765*** (-7.90)
Liquidity	-.03697*** (-6.68)
Constant	.0239*** (14.78)

Number of obs.	853
F (5, 847)	69.54
Prob > F	0.0000
R-squared	0.2910
Adj R-squared	0.2869

Table 3. presents the regression results for the CAMELS variables only. The superscripts ***, **, * indicate significance at 1%, 5%, 10% respectively.

The adjusted R-squared for this second model is equal to 28.69%.

4.5 Regression with both structural and CAMELS indicators

Purpose of this thesis is to address the credit spread puzzle issue, trying to provide empirical evidence to the literature with more findings regarding the presence, or not, of the puzzle. By running a third regression where both the structural variables groups are considered the analysis aims to answer the following two questions:

5. Do the CAMELS indicators provide incremental evidence than the structural variables regarding a banks' financial position?
6. Is the credit spread puzzle – in my sample – due to just the non-exhaustive explanatory power of the structural variables?

In order to address these topics, it is run a linear pooled regression with all variables in it. The formula of this third regression will then be: $Y = \alpha + \beta X + \gamma Z$. Where Y are CDS spread levels, X represent the structural model variables and Z stand for CAMELS indicators.

The only non-significant variable from a statistical perspective remains the management quality, which in this study is not a factor affecting the CDS spread differently from the findings of Hasan et al. (2014).

Table 4. Regression with both structural and CAMELS variable

	Coefficient
Leverage	.0121*** (4.13)
Volatility	.0216*** (8.57)
Risk-free	.43623*** (16.75)
Cap. Adequacy	.06833*** (6.20)
Asset Quality	-.11283** (-2.01)
Manag. Quality	-.00008* (-0.11)
Earnings	-.0239*** (-8.04)
Liquidity	-.01517*** (-2.96)
Constant	-.0206*** (-5.38)

Number of obs.	853
F (8, 844)	104.24
Prob > F	0.0000
R-squared	0.4970
Adj R-squared	0.4922

Table 4. presents the regression results for both structural and CAMELS variables. The superscripts ***, **, * indicate significance at 1%, 5%, 10% respectively.

The most interesting measure showed in this regression is the explanatory power. R-squared adjusted is equal to 49,22%, which is 7 percentage points higher than the model explained by the structural Merton one. This finding means that including both structural and CAMELS variables improves the model fit from 42,75% to 49,22% consistent with the hypothesis developed in this study, suggesting that CAMELS indicators hold complementary information regarding a bank credit risk, to respond to the research question number one. To answer research question number two, the R-squared level is still far from the 100% indicating that the credit spread puzzle – in the model – still represents an issue. In other words, there is a robust part of the bank credit risk that is not explained by both structural and CAMELS variable.

4.6 Impact of crisis

In this section the model aims to investigate the impact of the crisis upon structural model's variables, particularly volatility and leverage. Since the sample consists of European Banks the crisis accounted for is the sovereign debt one, witnessed in the period 2010 – 2012. It is then added a dummy variable to account for crisis periods which takes value 1 for those observation that fall within the crisis timeframe otherwise the variable takes value 0. Afterwards new variables are created through the interaction of the original variables and the dummy one. The new regression takes the following shape (same formula is applied for volatility as well):

$$CDS = \alpha * Leverage + \beta * (leverage * dummy\text{-}crisis) + \ldots$$

From the model specification, the coefficients should be read in the following way:

- α represents the leverage effect under non-crisis periods, since in this period β is going to be equal to 0;
- $(\alpha+\beta)$ will then reflect the effect during crisis periods.

Table 5. Regression with Dummy variable

	Coefficient
Leverage	.00266* (1.01)
Volatility	.03147*** (11.02)
Risk-free	.34707*** (16.39)
LeverageCrisis	.01374*** (5.28)
VolatilityCrisis	-.02514*** (-4.41)
Constant	-.00888*** (-4.17)

Number of obs.	853
F (5, 847)	138.75
Prob > F	0.0000
R-squared	0.4503
Adj R-squared	0.4470

Table 5. presents the regression results when the crisis is accounted for. The superscripts ***, **, * indicate significance at 1%, 5%, 10% respectively

Risk-free variable was not considered in conjunction with the dummy, since it is still not clear what should be the relationship with the credit default swap. Regarding the other two structural variables, they are both statistically significant. Leverage crisis' coefficient is higher than non-crisis periods, it is indeed equal to 0.016

(t = 5.28). This finding suggests that the negative impact of leverage is stronger during crisis period than non-crisis. On the other hand, the volatility variable under crisis is 0.0063 (t = - 4.41), lower than the non-crisis period within the sample size and the model design.

5 Conclusions

This study analyzes the determinant of the Credit Default Swap levels on a sample of 20 listed European bank. Banking industry does have a prominent role in the economic landscape especially after the financial crisis experienced in 2008; for this reason, it is crucial to perform some more work upon this sector from a credit risk point of view as well. Through an unbalanced panel data sample constituted by 853 observations, the work aims to understand the determinants of European banks' CDS spread.

First, it contributes to the literature by providing additional empirical evidences regarding the applicability of the structural model variable to price banks' CDS spread. The results suggest that all of them are economically and statistically significant, but still there is a percentage of the spread's variation that is not explained by those variables, consistent with the credit-spread puzzle theory. So, the analysis adds another group of variables represented by CAMELS indicators. Running the regression with only the six CAMELS variables suggests that – except for the management quality – all of them are both statistically and economically significant. Afterwards, it is run a regression with both structural and CAMELS indicators, and the explanatory power, measured by the adjusted R-squared, improved of 7 percentage points. This finding suggests that the CAMELS indicators hold incremental information beyond the structural variables.

However, there is a part of the model not explained by the variable picked, thus the credit spread puzzle is still an issue. Additionally, the study addresses the topic of the crisis by adding a dummy variable within the model. This variable interacts with both leverage and volatility. Findings are both statistically and economically significant and suggest that the negative effect of the leverage upon the CDS spread tents to be stronger during crisis period, while for volatility is the opposite.

To conclude, this study helps the current literature through its findings regarding bank's credit risk topics since the focus is more upon industrial companies than financial institutions. Furthermore, it provides the authorities with a new instrument – the Credit Default Swap – when monitoring the banking industry's stability. Those spreads can be used as warning alert tools that triggers the banks' supervisors to change their decisions according to the different alerts from the CDS market.

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