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Financial Technology Paper

The determinants of Credit Default Swap premia and the use of Machine Learning techniques for their estimation.

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This paper examines the determinants of Credit Default Swap premia. It also explores the use of Machine Learning techniques for their estimation. We address default risk, counter-party risk and liquidity risk. We discuss these in the context of yield curves, maturity and volatility. The insights gained are used to illustrate how the use of technology can provide more timely, efficient and informative valuations. We recommend the use of support vector and artificial neural networks (supervised learning models), as well as principal component analysis. Combined with standardized electronic processing and central clearing of trade, we suggest that this will enhance the depth of CDS markets. At the same time, Machine Learning can also aid the understanding of the various premia. We conclude that the application of Artificial Intelligence can add significant economic value to banking operations.

KEYWORDS
Credit Default Swap, Risk Premia, Machine Learning, Banking, Fintech, Financial Services, Disruption, Artificial Intelligence, Risk, Valuation, Derivatives.

Abbreviations: AI - Artifical Intelligence; AIG - American International GroupAmerican International Group; CDS - Credit Default Swaps; ML - Machine Learning; SVM - Support Vector Machine; US - United States.

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1 | INTRODUCTION

This paper examines the factors that determine Credit Default Swap (CDS) premia. It reviews the extent of both theory and practice in their pricing. It recommends suitable machine learning methods for their estimation. In an efficient market, CDS spreads should equal bond spreads. This is not always the case in practice. The functioning of CDS is described and explained in detail in order to demonstrate this as well as how Machine Learning can make their evaluation more efficient.

We clarify which are the key factors determining premia. These are divided into factors of default risk, counterparty risk and liquidity risk. The focus lies clearly on the default risk, since it accounts for the largest share of the premium. We introduce the theory behind no-arbitrage models, Structural Models and Reduced Form Models. This provides information on which risks influence CDS premium levels. We focus on the determinants of premia documented in empirical studies. We discuss these in the context of state-of-the-art algorithms.

We observe that CDS are one of the most significant financial market innovations of recent decades. Ever since their introduction in the mid-1990s, the market for CDS has grown significantly. They belong to the category of credit derivatives and facilitate the trade of credit risks. A CDS can serve as a kind of insurance or hedge against a company's or a state's (credit) default. For this insurance, the buyer of the CDS must pay a premium that is determined by many different factors, e.g. the default risk of the reference company. Especially during the financial crisis of 2007-2009, CDS received a lot of attention and have been controversial ever since. The subprime crisis that initially gave rise to the financial crisis has largely been attributed to CDS deals.

2 | BACKGROUND

There are a number of Financial Technology solutions that can improve CDS market efficiency and depth. CDS are traded over-the-counter (OTC) and not on an exchange or via the internet.[1] Terms are still agreed to individually between the contracting parties rather than automatically. The sellers on the market are mostly insurance companies or banks who are familiar with Financial Technology. As such, the market is ripe for improvement.

With the aid of a CDS, a buyer can hedge against the default risk of a certain company or state. CDSs can also be used for purely speculative purposes. They are thus an important tool for portfolio managers and investors who want to hedge their positions but also ripe for applying technological solutions.

The buyer of the CDS is referred to as the protection buyer and the seller as the protection seller. The respective company or state is called the reference debtor. An occurrence of default is referred to as a credit event and is typically defined as insolvency, default or restructuring of debts. This will be specified in detail before the emission. Generally, the standards of the International Swaps and Derivatives Association (ISDA), an association that is committed to secure and stabilise OTC trading of derivatives and has developed framework agreements for this purpose, are used as a guideline.

By purchasing a CDS, the bonds issued by the reference debtor to which the CDS relates can be sold to the protection seller at their nominal value when the credit event occurs. In the case of a coupon bond, the nominal value corresponds to the nominal amount that is repaid by the issuer at maturity in the event of default. A CDS contract may also relate to several bonds of the issuer. The total face value of the bonds that the protection seller must purchase in the event of a credit event is called the notional value of the CDS. However, in order to enter into CDS contracts, possession of the underlying bonds is not mandatory. To purchase protection against default, the buyer

[1] For further reading, Hull's (2015) textbook 'Options, Futures and other Derivates' is recommended.

only has to pay a premium to the seller until maturity or the credit event occurs, which is known as the CDS spread. Premia, measured in basis points of the notional amount of the CDS, are paid quarterly, semi-annually, annually or in advance, with quarterly payment being the most common. When the credit event occurs, the bonds are either physically delivered or, as is common practice, settled by cash payment.

Various types of CDS exist on the market, such as binary CDS, basket CDS or single-name CDS. With binary CDS, a predetermined amount is paid out when the credit event occurs. A basket CDS relates to several reference debtors. Depending on the type of basket CDS, payment is only made if either the first reference debtor (first-to-default CDS), the second reference debtor (second-to-default CDS) or the n^{th} reference debtor (n^{th}-to-default CDS) defaults. In contrast to the basket CDS, the single-name CDS is based on only one reference debtor. This type of CDS is the most common.

We address the single-name CDS in this paper. In addition, there are various CDS indices that show similarities to the aforementioned types of CDS. For these contracts, the hedging refers to the reference debtors listed in the index. If a reference debtor defaults, the contract is not terminated as with the single-name CDS, but continues until the end of the contract. The reference debtor is merely removed from the index, and the nominal amount is reduced accordingly. iTraxx, for example, is a family of CDS indices that cover the European and Asian markets and consists of the most liquid single-name CDSs.cf. Alexander and Kaeck (2008), p. 1008

Usually, a CDS contract contains an agreement that various bonds can be delivered. The reference bond then serves as a benchmark for determining which bonds are suitable for delivery. Since the bonds can be quoted at different prices, a cheapest-to-deliver bond option is linked to the CDS in this case. This means that the buyer can deliver the most favourable bond for him. If a cash settlement is agreed, an average market price of the bond is decided on a predetermined number of days after the occurrence of the default. This is calculated in an auction process organised by the ISDA. The difference between the average market price and the face value of the bonds is then paid to the protection buyer. For both physical delivery and cash settlement, payment of the premium is suspended from the occurrence of the credit event. If the credit event occurs between two payment dates, the premium accrued since the last date is paid. The following figure illustrates the aforementioned:[2]

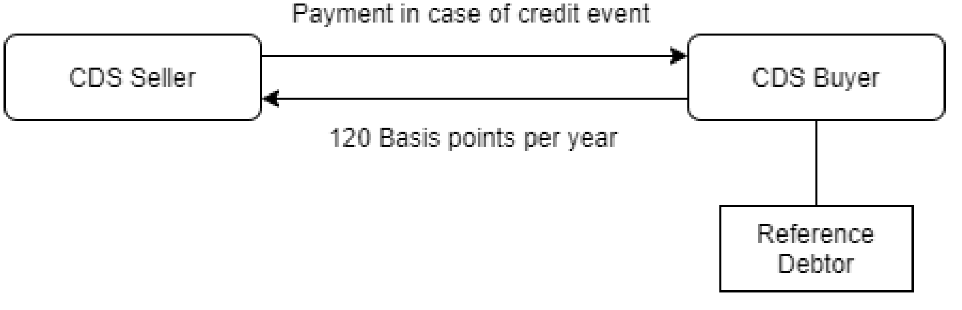

FIGURE 1 Functionality of a Credit Default Swap: *The figure shows the relevant parties for a CDS contract and their interaction with each other. The CDS seller pays out a predetermined amount to the CDS buyer if a credit event occurs with the reference debtor* (Feser, 2020).

In practice, the contracts often mature on standard dates such as March 20, June 20, September 20 or December 20 and the redemption date of the reference bonds or the desired hedging period may differ from those dates. CDS

[2] Restyled graphic following Hull (2015) p. 702

contracts with a five-year maturity are the most commonly traded. In general, maturities between 1 - 10 years are common.

In the illustration above, the bank offered the buyer a CDS with a premium of 120 basis points. When determining the premium, all risks associated with the CDS must be taken into account, as these are decisive for the amount of the premium. These include the default risk, the counter-party risk and the liquidity risk.

In the context of CDS, the default risk comprises the risk that the reference debtor becomes insolvent. Since the CDS hedges the secured party for precisely this case, the risk must be factored into the premium. Since the seller of the CDS bears the default risk of the reference debtor, he may be able to demand a higher premium for a substantial default risk than would be the case for smaller default risk.

Counter-party risk is defined as the risk that the guarantor defaults or experiences payment difficulties so that in the event of a credit event, the secured party does not receive the agreed payment. A CDS contract from a protection seller with a poor credit rating and thus with a high default risk could, therefore, be worth less than a contract from a protection seller with a better credit rating. For this reason, the premia charged by sellers of CDSs with a poor credit rating may be lower than comparable contracts from sellers with a better credit rating. CDSs are affected by counter-party risk because they are traded OTC. Therefore there is no central counter-party between the parties to the contract.[3] The example of the insurance group American International Group (AIG) demonstrates that this risk is not negligible. Since the financial crisis of 2008, this has become even more evident. However, the counter-party risk can be reduced by providing collateral. Since the value of the CDS contract can change during the term, for example due to an increase in the default risk of the reference entity, the seller provides the buyer with a security deposit as collateral, which typically consists of a cash payment or government bonds.

In the case of CDS, liquidity risk refers to the fact that liquidity in the market deteriorates. Liquidity generally indicates the degree to which CDS can be traded quickly and in any volume without significantly changing the current price. In illiquid markets, it is difficult to find a counter-party. The lack of supply in illiquid markets could lead to higher premia than in more liquid markets.

The influence of the above-mentioned risks on the determination of premia is examined in the following chapters. To this end, factors relating to the individual risks are examined. In order to understand which factors these are and how they are related to the risks, an initial overview will be provided, laying out some relevant theoretical models. Later on, methods from the field of neural networks, which are suitable for premia estimation, will be presented.

2.1 | Corporate Bond Market

We address the corporate bond market because this is where the potential for efficiency gains is greatest and hence Machine Learning could have the biggest impact. With swaps based on corporate bonds, both CDS premia and bond yield spreads are influenced by the default risk of the underlying company. This is taken into account during the respective price determination. For this reason, there should be a correlation between a CDS and the bond of the reference company to be observed. In the case of an arbitrage-free valuation, the premium corresponds approximately with the yield spread of the reference bond with the same maturity $(s = y - r)$. In the following, we will examine whether this correlation also applies in reality and what significance premia have for the corporate bond market.

Blanco et al. (2005) examine in their study the relationship between CDS premia and yield spreads of bonds issued by 33 European and US companies for the period from January 2001 to June 2002 and show that the yield spreads of the reference bonds are in most cases approximately equal to the premia, which suggests a close correlation. Longstaff et al. (2005) and Hull et al. (2004) also present empirical evidence suggesting that the relationship is very

[3] cf. Cecchetti et al. (2009), p. 46

close. Thus, the no-arbitrage relationship established seems to apply approximately in reality. The yield spread of a bond compensates the buyer for the risk assumed, compared to a risk-free bond.

As the work of Huang and Huang (2012) suggests, the default risk of the company makes up part of the yield spread. The higher the default risk of the company, the higher the yield spread must be to compensate the buyer for the risk taken. In the case of the CDS premium, the same correlation applies, although in the case of CDSs, the seller bears the risk. This shows why, in the no-arbitrage setup, the premium also rises as the yield spread increases.

The close relationship observed between the CDS premium, and the yield spread of the reference bond raises the question of the extent to which the two prices influence each other or which of the markets is the price leader. A price-leading market is characterised by the fact that the determination of prices is not influenced by other markets, but solely by new information relevant to the market. The market which is not price leader reacts to the price change of the other market until a new equilibrium is established.

Blanco et al. (2005) show in their already mentioned study that the CDS market leads the corporate bond market in pricing. They argue that, unlike other markets, the CDS market offers the best opportunity to trade credit risk. For example, it is easier to trade large volumes in the market. Because, for the reasons given above, the CDS market has higher trading activity and therefore greater liquidity, pricing is more likely to take place in this market. Similarly, Zhu (2006) concludes that the CDS market has the lead over the corporate bond market in the price discovery process. Thus, the CDS market helps to improve the efficiency of pricing default risks.

Then again, not only is the CDS market generally more liquid than the corporate bond market, but according to Das et al. (2014), it even withdraws liquidity from the market. They found that after the introduction of CDS, the trading volume of bonds declined, with trading volume serving as a proxy for liquidity. They argue that large institutional traders have switched from the corporate bond market to the CDS market. This switch could, as a result, be the reason for the withdrawal of liquidity. There are also other studies examining the impact of CDS on bond markets, however, these will not be investigated further here.

In summary, it can be stated that the premia are closely related to the yield spreads of the benchmark bonds. For the most part, the CDS market has price leadership over the corporate bond market, which is why new information is more quickly reflected in CDS premia.

3 | THE THEORY BEHIND VALUATION OF CDS PREMIA

Different valuation models of CDS premia are discussed in the relevant literature and can all be built into an algorithm that can be automated. A standard method is a valuation using a no-arbitrage model. In addition, CDS premia can also be valued using credit risk models because the default risk of the reference debtor is an essential factor in the premium. These can be divided into two main categories: Structural Models and Reduced Form Models. The models can be used to identify which risk factors can theoretically determine CDS premia.

3.1 | No-Arbitrage Models

In theory, derivatives can be valued using no-arbitrage models. These models are based on the principle that financial instruments must be valued in such a way that no-arbitrage possibilities exist. A simple no-arbitrage relationship can be shown using the relationship between CDS premia and bond yields. In theory, the premium should be related to the yield spread of the reference bond, i.e. the difference between the yield of a risky and a risk-free bond. This relationship can be compared with

$$s = y - r$$

The y here signifies the par yield of a bond of the reference debtor with a maturity of n years. The par yield is the coupon interest rate, which equates the bond price with the nominal value of the bond. The r stands for the par yield of a risk-free bond with a maturity of n years and the s for the premium of a CDS with the same maturity. The combination of a CDS and a bond of the reference debtor creates approximately a risk-free bond because the buyer of the CDS hedges against the risk of default. For this reason, the above equation must apply in theory to avoid arbitrage opportunities.

If s is greater than $y - r$, an arbitrageur could sell the CDS, short the underlying corporate bond and buy the risk-free bond. If s is smaller than $y - r$, he could buy the corporate bond and the CDS and short the risk-free bond. In this case, the arbitrageur obtains a higher return by buying the corporate bond and the CDS risk-free than he would with the risk-free bond.

For this arbitrage consideration, however, many assumptions or simplifications have to be made. For example, it is assumed that corporate bonds and risk-free bonds can be sold short, whereby the short sale of risk-free bonds is equal to borrowing at a risk-free interest rate. It is also assumed, among other things, that interest rates are constant so that the par yield does not change. This, however, is not always the case. Moreover, the cheapest-to-deliver bond option and counter-party risk are neglected. As the initial example with AIG has shown, counter-party risk should not be neglected in determining the premium.

Thus, the above-mentioned no-arbitrage setup is only an approximation of reality due to the assumptions made. Despite the assumptions, it can be seen from the model presented that the risk-free interest rate and the bond yield of the reference company are two determining factors of CDS premia. The higher the yield of the reference bond, the higher the CDS premium must be (with unchanged r), or the more significant the bond yield spread over a risk-free bond, the higher the premium. Consequently, the lower the risk-free interest rate, the higher the premium must be. The bond yield is therefore assumed to be positive and the risk-free interest rate negative. In this case, this is initially based purely on the idea of arbitrage. How these effects can be explained in economic terms will be discussed in the following chapters.

3.2 | Structural Models

The default risk of a company, and thus the associated CDS premium, can be assessed using Structural Models. These use company-specific data to assess the default risk. The default risk depends on the change in the market value of the company's assets. It is assumed that the value of the assets develops randomly. According to the theory, the company fails precisely when the value of the assets falls below a default limit, whereby the default limit can be either endogenous or exogenous. For example, it can be assumed that insolvency occurs when the amount of liabilities exceeds the value of the company. Structural Models are based on the Black-Scholes-Merton model (1974) and are more precise, using their option price theory to assess the default risk of fixed-income securities.

The focus of the Structural Models lies on the default risk. In these models, the main determinants of the probability of default are volatility, the company's leverage and the risk-free interest rate. If the market value of the company falls, the probability of default increases because it becomes more likely that the default limit will be exceeded. The more volatile the value of the company, the more likely it is that the default limit will be exceeded. If it fluctuates strongly, the limit can be exceeded more quickly. However, since the volatility of the enterprise value is difficult to monitor, stock volatility can be used for this purpose. This variable is a good substitute since there is a positive correlation between stock volatility and company value volatility. If it is assumed that the higher the probability of default of the reference debtor is, the higher the premium, then this must also increase with an increase in volatility. If the possibility of default is high, the protection seller who bears the risk of default, takes a high risk and must be compensated accordingly.

- A positive correlation can also be assumed for the gearing ratio. It indicates the percentage of debt in a company's total capital. The higher the gearing ratio of a company, the higher its probability of default. Therefore, the greater the gearing ratio, the higher the premium would have to be.

- A negative correlation can be assumed for the risk-free interest rate and the CDS premium. In the theoretical model, an increase in the risk-free interest rate leads to a reduction in the probability of default. Consequently, the premium for the CDS also falls. This correlation seems plausible, since low interest rates occur, for example, in times of economic crisis or during a recession. In these times, the default rates of companies are particularly high.

How the risk-free interest rate will change in the future can be estimated using the yield curve. The steeper this curve is, the higher will the expected interest rates be in the future. From the relationship between the premium and the risk-free interest rate, it can now be derived that there must also be a negative relationship between the slope of the yield curve and the premium.

Rising interest rates in the future are also a sign of increasing economic activity, which provides an additional argument for the negative correlation. The greater the slope, the better the expected economic situation. If, on the other hand, it is very flat, economic activity is expected to decline. This could lead to rising premia due to the increased probability of default. Thus, a negative correlation is expected overall. A more in-depth discussion is provided in section 4.1.4.

3.3 | Reduced Form Models

In reduced form models, the time of default of a company is assumed to be unpredictable and random. This is based on an underlying probability distribution. The insolvency of a company is therefore not explained by economic correlations as in the Structural Models. For the models, the default risks can be deducted or estimated on the basis of market prices for corporate bonds. In practice, the probability of default is often determined on the basis of ratings. The better the rating, the lower the likelihood of default.

One model based on the intensity models comes, for example, from Hull and White (2000). According to their model, the premium of a CDS with an assumed nominal amount of £1 is calculated as follows: First, the assumptions must be made that the risk-free interest rate, the credit events and the recovery rate are independent of each other, so that these variables are easier to compute. The recovery rate is the remaining value, expressed as a percentage of the face value, of a bond issued by the reference entity after the credit event. It is also assumed that the CDS buyer's claim in the event of a credit event consists of the sum of the nominal amount and the accrued interest. It is also assumed for the model that there is no counter-party risk. The risk-neutral probability that no credit event will occur during the term of the CDS is determined by

$$\pi = 1 - \int_0^T q(t)\,dt$$

where, $q(t)$ stands for the risk-neutral probability density of default at time t and T for the term of the CDS. $\int_0^T q(t)dt$ indicates the risk-neutral probability that a credit event will occur up to time T. If it occurs at time $t(with\ t < T)$, the present value of the premium payments is:

$$w[u(t) + e(t)]$$

where, $u(t)$ is the present value of the premium payments per year on payment dates between 0 and t (calculated for £1) and $e(t)$ is the present value of the premium payments at time t that have accrued between $t - t*$ ($t*$ is the payment date before t). w denotes the total premium payments per year. The premium payments end either when the CDS expires at time T or when the credit event occurs. If no credit event occurs during the term of the CDS, the present value of the premium payments is $wu(t)$. Thus, the expected present value of the premium payments can be calculated as

$$w\int_0^T q(t)[u(t) + e(t)]dt + w\pi u(T)$$

The risk-neutral expected payout from the CDS (for a nominal amount of £1) is

$$1 - [1 + A(t)]\hat{R} = 1 - \hat{R} - A(t)\hat{R}$$

$A(t)$ represents the accrued interest of the Reference Bond at time t, expressed as a percentage of the principal amount. $\hat{R}$ indicates the expected recovery rate independent of the time of default. The present value of this risk-neutral expected payout is

$$\int_0^T [1 - \hat{R} - A(t)\hat{R}]q(t)pv(t)dt,$$

where, $pv(t)$ is the present value of £1 received at time t. The buyer's value for the CDS is

$$\int_0^T [1 - \hat{R} - A(t)\hat{R}]q(t)pv(t)dt - w\int_0^T q(t)[u(t) + e(t)]dt - \pi wu(T)$$

The value is the difference between the present value of the expected payout and the present value of the premium payments to the CDS seller. These two cash values must match so that neither the buyer nor the seller of the CDS has an advantage over the other. w must, therefore, be chosen in such a way that the two present values balance each other out. The value of w that meets the condition is the CDS premium s. This equates from

$$s = \frac{\int_0^T [1 - \hat{R} - A(t)\hat{R}]q(t)pv(t)dt}{\int_0^T q(t)[u(t) + e(t)]dt - \pi u(T)}$$

The premium, in this case, is defined as the annual amount payable by the secured party, expressed as a percentage of the nominal value of the CDS.[4] The model presented here serves as an entry-level model and can be extended, for example, with an arbitrage approach, to achieve more precise results. However, in order to get a first overview of the

[4] cf. Hull and White (2000), p. 34

determining factors of CDS premia, in theory, this model is sufficient without extensions.

The model shows that the probability of default of the reference company, the recovery rate and the term of the CDS are among the factors determining the premia. Since the present values are used for calculation here, the discount rate also influences the level of the premia. The level of the coupon interest rate of the reference debtor is also decisive, since, e.g. in $A(t)$ the accrued interest is taken into account.

The formula for s shows how these factors influence the premium. The higher the probability of default of the reference debtor, the higher the premium. As already mentioned, the seller has to be compensated according to the risk, which is why he also demands a higher premium if the probability of default is higher. The higher the recovery rate, the lower the premium. This is because the higher the recovery rate, the lower the expected payment from the protection seller to the protection buyer. The premium also increases with the term of the CDS, since the probability of default in the model is greater for the long term than for a shorter one.

To show what influence counter-party risk has in theory on the valuation of CDS, Hull and White (2001) use an extension of the model presented above. This is also used to determine the premium. If the default of the protection seller and the reference debtor are uncorrelated, the influence of the counter-party risk in the model is very small. This is understandable since a default of the reference entity does not influence the counter-party's default risk. However, the impact of the counter-party risk becomes more significant as the correlation increases and the default risk of the protection seller increases.

The models presented show some risk factors that determine premia in theory. These include the risk-free interest rate, the slope of the yield curve, volatility, leverage, coupon rate or yield of the reference bond, probability of default, recovery rate, CDS maturity, discount rate and counter-party default risk. The extent to which some of these factors have an influence in reality and which factors also determine the level of premia will be examined below.

4 | DEFAULT RISK

As already mentioned, the amount of the premia depends on the default risk, the counter-party risk and the liquidity risk. However, there are no clear indicators for these risks that can be observed on the market. For this reason, proxies must be used to examine the influence of the individual risks on the determination of the premia, which relate to the respective risk. Many studies deal with the determining factors of premia. The research aims to find out with the help of regression analyses whether and how strongly certain factors influence the premium level. Some of the factors that are used in the analyses as explanatory variables for the premia will now be examined and discussed in more detail. These are assigned to the three risk types hereinafter.

The default risk has the most significant influence on premia in the theoretical models. Whether this is also true in reality and how exactly it affects the premia will be investigated using the proxies leverage ratio, CDS maturity, risk-free interest rate, slope of the yield curve, volatility and rating. Although many other influencing factors that can be assigned to the risk of default are tested in studies, these are not part of the work at hand, but might offer further potential for the application of machine learning algorithms.

4.1 | Debt Ratio/Leverage

Based on former studies, it can be assumed that the debt ratio has a statistically significant influence on premia; for example, Ericsson et al. (2009) are to be mentioned here. To this end, they examine CDS premium notations of mostly US companies for the period 1999-2002 and observe a positive correlation between the gearing ratio and the premium. This correlation is plausible since the risk for the hedge provider increases with a rising debt ratio and thus a rising probability of default. Therefore, the hedge provider demands a higher premium. In the study, the effect of the gearing ratio is greater for companies with a low rating than for those with a higher rating. If the gearing ratio increases by 1% for companies with a low rating, the premium of the corresponding CDS increases by approximately 6-10 basis points, if all companies are considered, the effect is 4.8-7.3 basis points. Ericsson et al. (2009) also examine the impact of risk-free interest rate and stock volatility on premia and find that a gearing ratio of R^2 between 31.7% and 45.7% best explains premia.

Aunon-Nerin et al. (2002) and Baum and Wan (2010) exemplify that the debt ratio has a statistically significant influence on premia. In line with expectations, the correlation is also positive here. Furthermore, Baum and Wan (2010) show in their study, in which they examine the CDS premia of 527 companies for the period between January 2001 and December 2006, that, as in Ericsson et al. (2009), the effect of the gearing ratio is higher for companies with a lower rating than for better-rated companies. It can be concluded that a change in the gearing ratio has less of an impact on the probability of default for companies with a good rating than for those with a poor rating.

Galil et al. (2014) note that during the financial crisis, leverage had a more significant impact on premia than before and after the financial crisis. In their study, they examine 718 US companies and use the years 2002-2007 for the period before the financial crisis, 2007-2009 during the financial crisis and 2009-2013 after the financial crisis. The effect of volatility is statistically significant for all periods. It can be deduced from the result that premia could generally react more sensitively to the level of debt in turbulent market phases than in quieter stages. One reason for this could be that the fear of default is particularly significant in turbulent times. Therefore the risk of default, measured here by the debt ratio, is taken into account to a greater extent in the premium.

It can be shown from the studies that the debt-equity ratio is an important determinant of the premium. The higher the gearing ratio, and thus the default risk, the higher the premium.

4.2 | Maturity

In empirical studies, the CDS's maturity as a factor influencing the premium remains controversial. Aunon-Nerin et al. (2002) examine CDS premium quotations of 70 states and 323 companies from different countries for the period from January 1998 to February 2000 and find that the maturity is seldom statistically significant. In addition to the overall sample, they examine subsamples consisting of all companies, only US companies, non-US companies and states where the maturity has a significant influence only in the overall sample. In the sample where it is significant, it has a positive correlation with the premium. According to this finding, the longer the time to maturity, the higher the premium. A longer duration entails a higher degree of uncertainty. This could be one reason for the higher premium.

This correlation is consistent with the valuation model of Hull and White (2000) presented above, in which the premium also increases with maturity because a longer maturity leads to a higher probability of default. The point that the maturity in only one sample is significant could be due to the fact that many of the CDSs under consideration have a maturity of five or just under five years. The result might have been different for a sample of many different maturities or would have produced more precise results concerning the effect of maturity. Aunon-Nerin et al. (2002) also asked whether the maturity of reference debtors with a high rating has a different impact than that of those with a low rating. However, even here, the results are not significant, which could be due to the reason already mentioned. Abid and Naifar (2006) conclude in their study that the term has no significant influence on the premium. They examine the CDS premia of 73 different companies from different European countries for the period from May 2000 to May 2001. Here, too, could the reason for the result be the main investigation of contracts with a term of five years.

Fabozzi et al. (2007) even conclude in their regression analysis that there is a negative correlation between the term and the premium. Surprisingly, for the period from 2000 to 2003, this correlation is statistically significant in all years except 2001. However, a negative and significant correlation contradicts the expectations of the theory. The decisive factor for the result could also be that the term is usually five years. From the results of the studies, it can be concluded that there is no clear correlation between the duration of the CDS and the premium.

4.3 | Risk-free Rate

Empirically it can be shown that the risk-free interest rate influences the premium. Since there is no generally valid risk-free interest rate, various proxies are used in the regression analyses. Ericsson et al. (2009) use the yield of 10-year US government bonds for the risk-free interest rate. A negative, statistically significant correlation between the yield and the premium is pointed out. The negative correlation was already addressed in the Structural Models and is substantiated by this study. The higher the risk-free interest rate or proxy, the lower the default risk and thus the premium. They also find that the risk-free interest rate has a stronger effect on lower-rated companies than on better-rated companies. This is therefore the same effect that is found for the leverage ratio. Overall, the risk-free interest rate has a somewhat lower explanatory power than the gearing ratio. The R^2 lies between 28.2% and 40.1%.

Aunon-Nerin et al. (2002) also find a statistically significant negative correlation between the risk-free interest rate and the premium, but come to a different conclusion regarding the effect of the interest rate on well and poorly rated companies. They observe that the risk-free interest rate has a much higher influence on the premium for US companies with a high rating than for US companies with a low rating. For the latter, the effect turns out to be insignificant. One reason for the different results of the two studies could be that different interest rates with different maturities are used. The reason why Aunon-Nerin et al. (2002) come to this conclusion could be that when interest rates rise, financing costs increase. The companies in the sample with a poor rating react more sensitive to this than the better-rated companies. Rising financing costs can lead to an increasing probability of default. The higher financing costs compensate for the fact that, according to the theory, companies with higher interest rates should have a lower likelihood of default and thus lower CDS premia. This compensation ultimately leads to a smaller interest rate effect on the premium.

Further, it is presented by Aunon-Nerin et al. (2002) that the chosen American risk-free interest rate has a significant influence not only on the premia of US companies but also on the premia of states and on those of the companies investigated outside the USA. This result could mean that the risk-free US interest rate is regarded as a global risk-free interest rate and is therefore an essential factor in determining premia outside the USA. In contrast, the study by Abid and Naifar (2006), in which the selected American risk-free interest rate has no significant effect on the premia of European reference companies, contrasts with a risk-free European interest rate. In this study, the American risk-free rate corresponds to the yield on three-month American Treasury bills, and the European risk-free rate to the yield on three-month French Treasury bills. The different results of the two studies could stem from the fact that different risk-free interest rates were used. To sum it up not every American interest rate that is considered risk-free is suitable for determining premia.

Fabozzi et al. (2007) and Alexander and Kaeck (2008) also find a statistically significant, negative correlation between the risk-free interest rate and the premium. Alexander and Kaeck (2008) also conclude that the short-term risk-free interest rate has a different effect on the premium depending on the sector. In the financial industry, the impact of the short-term interest rate is not found to be significant, unlike in the other areas considered, which may be because interest rate changes here act in two different ways. On the one hand, interest receipts increase when short-term interest rates rise, while on the other hand short-term financing costs also rise. Because banks and other financial companies refinance themselves more short-term than other companies, a change in the short-term interest rate has a more substantial effect there. The positive and negative effects of an interest rate change thus appear to cancel each other out in the financial sector. In the other sectors, where the effect of the risk-free interest rate is significant, it shows a negative correlation with the premium. The result is consistent with both theory and other studies.

In recent years several lenders were able to issue debt with close-to-zero or even negative yields. If one follows the studies described above, as well as the Structural Model, and the negative correlation between risk-free interest rates, the negative-yield territory should lead to heightened CDS premia. If the question is approached from a macroeconomic perspective, low interest rates can be used to finance otherwise unprofitable projects. This, again, increases the interest rate risk for the borrower and thus, for example, the default risk of the bond issuer.

As already mentioned in connection with default risks, a large number of studies show that this leads to higher premia. Following, the influence of negative-yielding debt might be indirect. This area has so far received little attention in academia and offers potential for future studies. Apart from this, the issue could also be further investigated in the light of Quantitative Easing, namely to what extent additional liquidity influences the demand for hedges, especially CDS. In his pioneering dissertation Zhang (2018) concludes that "The effect of the QEs on the hedging effectiveness and hedging performance of international bond portfolios depends on the choice of hedging strategy and the development level of the country in which a financial market is situated." Furthermore, the question arises whether hedges are sensible and efficient or merely redundant in a market with a regularly recurring large buyer. These questions cannot be discussed in depth at this point but should be considered in the context of the influence of the risk-free interest rate on CDS premia.

The results of the studies evince that the risk-free interest rate plays an important role in determining the premium. In principle, there is a negative correlation with the premium. However, the effect of the interest rate is not entirely clear for companies with a poor rating and for banks and other financial companies. When using risk-free interest rates in valuation models, care must be taken to select an appropriate interest rate. The last decade with its negative interest rates, as well as the decision of the FED to buy junk bonds within the framework of Quantitative Easing open up new questions about the interaction of risk-free interest rates and CDS premia.

4.4 | Yield Curve

The yield curve shows the applicable interest rates for short, medium and long-term bonds. Typically, a yield curve includes government bonds with (residual) maturities of one, two, three and ten years. Long-term interest rates are normally (normal yield curve) higher than the corresponding short-term interest rates. This is explained with expectation uncertainty or with a liquidity premium. In the case of the inverse interest rate structure, the interest on securities is lower with increasing maturity, as has been the case for US Treasury Bonds e.g. in 2019. Abid and Naifar (2006) conclude that the slope of the yield curve has a significant influence on the premium. It shows a negative correlation with the premium, which is in line with the theory. They calculate the slope here-in as the difference between the yield on a long-term European bond and a short-term French interest rate.

Aunon-Nerin et al. (2002) also find a significant negative correlation between the premium of CDSs in US companies and the slope. When considering the groups all companies, non-American companies and states, the slope is again not significant. This could be since American interest rates are used to calculate the slope, which consists of the difference between long-term and short-term interest rates. If local interest rates are used, however, the effects are significant. One explanation for this result might be that the US economy is developing differently from the economies of the countries under consideration outside the US. Since the slope of the yield curve can be seen as an indicator of future economic development, local interest rates would have to be used as a basis if economic developments in the countries were different. The result indicates that the risk of default is closely related to the state of the respective economy.

So far, there is not yet a sufficient number of studies on the effects of an inverted yield curve on CDS premia. Following the outcomes of e.g. Aunon-Nerin et al. (2002) premia would be high, this is in line with some studies using the inverted yield curve as an indicator for recessions, since heightened recession fears lead to higher premia. It is therefore again possible that indirectly the increased credit risk will lead to an increase in the premium. A careful assessment could, for example, examine the credit curve bootstrapped from CDS prices and test the different factors' influence. However, this is a challenging task, as the various factors are often interdependent or mutually reinforcing.

Overall, it can be stated that the slope of the yield curve is an important factor determining the premium. The higher the slope of the yield curve, the lower the premia. Here, too, care must be taken to select suitable interest rates for the calculation.

4.5 | Volatility

According to the Structural Models, stock volatility should be positively correlated with the premium. In their study, Ericsson et al. (2009) calculate volatility based on daily returns and find that it has a significant influence. As expected, there is a positive correlation between premium and volatility. When all observed companies are considered, an increase of 1% in annualised volatility leads to an increase in the premium of approximately 0.8-1.5 basis points. The effect is more significant for companies with a poor rating, where it increases by about 1.1-2.3 basis points. This correlation, which is also found in the leverage ratio, could mean that a change in volatility has a greater impact on the probability of default of companies with a poor rating than on those with a good rating. Compared with the effects of the risk-free interest rate and the gearing ratio, which were also examined in the study, equity volatility has the least explanatory power with an R^2 between 23.9% and 29.7%.

Alexander and Kaeck (2008) also conclude that overall volatility has a significant influence on the premium. In the study, they analyse the effect of implied volatility, based on current values for stock options, and historical volatility, based on historical daily stock returns, on the above-mentioned iTraxx indices for Europe. When considering the European index, the sub-indexes non-financial institutions, financial institutions with senior debt, financial institutions with subordinated debt and a high-volatility index consisting of the companies with the widest CDS spreads, they find that the implied volatility has the strongest effect on the high-volatility index and then on the European index. The result can be explained by the fact that both indices are the most volatile iTraxx indices. Changes in implied volatility are thus incorporated into more volatile indices more quickly. It can also be deduced from this that the premium may react more sensitively to changes in volatility in volatile market phases than in quieter market phases. This finding is supported by the results of Galil et al. (2014). In this study, volatility during the financial crisis had a greater impact on premia than before and after the financial crisis.

According to Alexander and Kaeck (2008), historical volatility has no significant influence on premia. This could be related to the fact that it is based only on historical values, whereas the implied volatility reflects expected future changes in the index. Benkert (2004) also concludes that implied volatility is better suited than historical volatility to explain premia. Why historical volatility in the study by Zhang et al. (2009) turns out to be significant, however, could be due to the different methods of calculating volatility, among other things. Furthermore, Alexander and Kaeck (2008), in contrast to Zhang et al. (2009), use indices for premia and apply a difference-in-differences regression, in which the individual levels of the variables and premia are not considered, but only their changes.

In summary, it can be said that volatility is an important factor in determining premia. The greater the volatility, the higher the premium. Since the probability of default increases with rising volatility, it is also the case here that the greater the default risk, the higher the premium.

4.6 | Rating

In practice, the ratings produced by rating agencies are often used as a benchmark for the default risk. They are one of the most important sources for assessing the creditworthiness of borrowers.

Abid and Naifar (2006) show in their study that the rating has a significant influence on the premium. When investment grade rating classes Aa_2, Aa_3, Baa_1 and Baa_2 are considered, the premium shows a positive correlation with the two better grades and a negative correlation with the two worse classes. The term investment grade comprises bonds with with good to very good issuer's solvency. In grades this equals BBB (S&P)/Baa_3 (Moody's) to AAA/Aaa, whereas the latter hold the highest grade. Fabozzi et al. (2007) come to the same conclusion in their study. From this, it can be concluded that the worse the rating, the higher the premium and vice versa. The results are, therefore, in line with expectations.

In addition to the above observations, Aunon-Nerin et al. (2002) also show that the rating has a more significant effect on the premium for sovereigns than for companies. Such a result confirms the insight found in the literature that ratings of states are not the same as ratings of companies. In their study, the rating has the greatest explanatory power compared to the other variables examined. In the overall sample of US companies, the R^2 47%, with the other variables considered (variance of share prices, debt ratio, maturity, risk-free interest rate) together only amounting to a $R2$ of 31%. The rating has a high explanatory power because rating agencies take many factors into account in their preparation, such as the financial strength of the company, the quality of management, the general state of the industry and the competitive situation.

Corò et al. (2013) find out in their study that during the financial crisis, changes in the rating had a much higher effect on changes in premia than before the financial crisis. They examine European companies from different industries and use the years 2006-2007 for the period before the financial crisis and 2007-2009 during the financial crisis. The reason for this could again be that in turbulent market phases, the fear of a default of the reference company is particularly high. Therefore the premia react more sensitively to changes in the default risk. Surprisingly, the effect of the rating was only statistically significant during the financial crisis. However, this contradicts the results of the studies presented so far. One reason for the deviation could be the use of different samples.

Hull et al. (2004) in their study, which only examines companies rated by Moody's in the period from October 1998 to May 2002, state that the CDS market anticipates negative rating decisions days before they are announced. For example, if all the companies examined are considered, the premia increase by approximately 38 basis points 90 days before a rating downgrade. At the same time, before the rating agency publishes a negative outlook for a reference company, they increase by about 29 basis points. Before a review for a downgrade, they increase by about 24 basis points.

The results show that the rating is a crucial factor in determining the premium. The worse the rating, the higher the risk of default and therefore, the premium.

4.7 | Discussion

Almost all of the default risk proxies examined here have a statistically significant influence on the premium. Consequently, it can be concluded that the default risk is an essential component of the premium. The greater the default risk, the higher the premium. So far, however, we have only investigated how the proxies individually affect the premium. To find out what proportion of the entire default risk is involved in determining the premium, the combined influence of the factors on the premium must be investigated.

Using leverage, volatility, and the risk-free interest rate to explain the changes in premia, the R^2 in the study mentioned above by Ericsson et al. (2009) is approximately 23%. When examining premium levels, the three proxies of default risk have an explanatory power of about 60%. In the study by Aunon-Nerin et al. (2002), in the overall sample of US companies, the variance, leverage, maturity, risk-free interest rate and rating together have an explanatory power of 65% (when examining the levels of premia).

Overall, it can be stated that the default risk accounts for a large part of the premium. However, it is also clear that it cannot explain the full amount of the premium. Thus, other risks, such as counter-party risk and liquidity risk, may also be included in the premium. These will be examined in more detail below.

5 | COUNTER-PARTY RISK

Counter-party risk is hardly taken into account in the theoretical models, which are mainly based on default risk. In reality, however, the risk may be more critical in determining the premium. In the following, we will explore the influence of counter-party risk on the premium.

Arora et al. (2012) show that counter-party risk is taken into account when determining the premium, but the influence is minimal. For the period from March 2008 to January 2009, they examine 14 large CDS sellers who offered CDSs on 125 reference companies. During this period, the fear of a default of the counter-party was unusually high due to the financial crisis, which is why the counter-party risk should then be particularly easy to measure. The sellers' premia were used to measure their default risk. There is a significant correlation between the default risk of the protection seller and the premia he offers for CDSs on other reference debtors. The higher the default risk of the guarantor, the lower the premia for the CDS offered. The result shows that the counter-party risk has only a very small impact on the premium. This could be due to the collateral that is often required in practice to reduce counter-party risk. The CDS sellers examined in the study typically provided full collateralisation or even minimal over collateralisation for both parties to the contract.

When the overall sample of reference companies is divided into the consumer goods, energy, industrial, technology and financial services sectors, it is found that counter-party risk is priced into the premium in all sectors except financial services. The result is surprising, as one would expect counter-party risk to be included, especially in the case of CDSs on financial institutions, because CDS sellers come from the same industry. Therefore the respective default risk should have a high correlation with the other. As the model of Hull and White (2001) shows, if there is a high correlation between the default risk of the reference debtor and the CDS seller, the counter-party risk should have a more considerable influence than if there is a lower correlation. One reason for the outcome might be that the reference entities (e.g. insurance and real estate companies) and the CDS sellers examined, although they are in the same industry, nevertheless exhibit substantial differences, and thus their default risks are not strongly correlated.

Since during the financial crisis, e.g. AIG got into payment difficulties and Lehman Brothers, among other banks, went bankrupt, one could assume that the influence of counter-party risk on premia has increased since the financial crisis due to a more substantial presence. Arora et al. (2012) show that the effect of counter-party risk has indeed changed. The influence of risk was twice as strong after the insolvency of Lehman Brothers as before. However, the effect is significant only at a significance level of 10%, but not at 5%.

The findings indicate that the counter-party risk has only a minimal influence on the premium, but it seems that the higher the counter-party risk, the lower the premium. The risk can be significantly reduced by using collateral.

Additionally, in the aftermath of the financial crisis multiple regulations were established to lower inter alia the counterparty risk. One example is the Basel III framework.

6 | LIQUIDITY

In macroeconomic textbooks, liquidity gives consumers the ability to trade with each other. But this definition usually only refers to the exchange of money, not other assets like derivatives. A perfectly liquid market would allow for the buying and selling of vast amounts of assets for equilibrium prices at any time. Liquidity might be scarce when a market participant wants to exit a position and, taking up the thoughts of Pastor and Stambaugh (2003), this is an important element of asset pricing.

In practice, a small bid-ask spread is a sign for a liquid market and represents an adequate measure. The liquidity risk is also not given much consideration in the theoretical valuation models for CDS premia. In order to explain the influence of risk, in reality, the bid-ask spread, the number of transactions and the number of buy and sell prices are used below as proxies for liquidity in the market. The bid-ask spread is the difference between the buy (bid) price that a protection buyer is willing to pay for the CDS and the sell (ask) price at which the protection seller offers the CDS. The lower the difference, the higher the liquidity in the market. A large bid-ask spread thus represents a high liquidity risk. The number of bid prices indicates the demand for CDSs and the number of ask prices indicates the supply of CDSs. The number of transactions represents the total liquidity in the market. The more transactions are concluded in a certain period, the higher the liquidity. In addition to the proxies mentioned above, many other factors of liquidity are examined in studies. However, their consideration would go beyond the scope of this paper.

6.1 | Bid-Ask Spread

The bid-ask spread is one of the most commonly used measures of liquidity. Fabozzi et al. (2007) find that the overall bid-ask spread in CDS quotes has a significant influence on the premium. The lower the bid-ask spread, the higher the premium. Thus, according to the study, CDS sellers can demand a higher premium when liquidity is high.

Corò et al. (2013) show, however, that the bid-ask spread has a positive, significant influence on the premium. Hence, the premium is higher, the larger the bid-ask spread or the less liquid the market is. Bongaerts et al. (2011) confirm this correlation in their study. According to them, the guarantor demands a liquidity premium. One reason for the divergent results could be that different time periods are considered. Fabozzi et al. (2007) consider the period 2000-2003, whereas Corò et al. (2013) consider the years 2006-2009 and Bongaerts et al. (2011) the years 2004-2008. Furthermore, Corò et al. (2013), in contrast to Fabozzi et al. (2007), do not examine the individual levels of premia and bid-ask spreads, but rather their changes.

The studies show that the bid-ask spread is an important factor in determining the premia. However, the direction of the correlation is not entirely clear and requires further examination.

6.2 | Number of Transactions

Fabozzi et al. (2007) show that both the number of bid and ask prices determine the premium in a statistically significant way. The number of purchase prices has a positive correlation with the premium. The higher the demand for CDS, the higher the premium. The number of ask prices has a negative correlation. Thus, premia decrease with increasing supply. The number of transactions is positively correlated with the premium. Thus, the higher the liquidity in the market, the higher the premia.

All studies examined, conclude that liquidity - measured as the bid-ask spread, number of transactions, and number of buy and sell prices - has a significant influence on the premium. Thus, when determining the premium, the liquidity risk is taken into account as an important determining factor. However, the correlation is not entirely clear. Some studies conclude that increasing liquidity leads to higher premia, whereas other studies show a negative correlation.

6.3 | Discussion

The influence of factors of liquidity risk (e.g. bid-ask spreads for the reference company and the industry, trading intensity) and default risk (e.g. degree of indebtedness, rating) in different market phases are examined in the aforementioned study by Corò et al. (2013). They find that liquidity factors have a higher influence on premia during the financial crisis (period of 2007-2009) than company-specific factors of default risk. Surprisingly, only the liquidity risk in the period before the financial crisis has a significant influence in the period of 2006-2007, but not firm-specific factors. Even if this observation contradicts the findings on default risk, which, according to the studies considered in this paper, had a statistically significant influence on the premium even before the financial crisis, it can nevertheless be deduced that not only the default risk is a decisive part of the premium. Many studies use the premium as a true measure of the default risk of the reference debtor, such as the study by Longstaff et al. (2005). This assumption can thus be refuted since the liquidity risk is taken into account when determining the premium. Thus, changes in the premia do not necessarily mean a change in the default risk of the reference debtor.

In summary, the empirical studies examined in this chapter have shown that the default risk of the reference debtor determines a large part of the premium. By contrast, the counter-party risk has only a very small influence, particularly due to the common agreement of security services. The liquidity risk is much more important in determining premia than it is assumed. Especially in turbulent market phases, liquidity risk has a major influence on the determination of premia. As indicated above, the liquidity risks' influence on CDS premia also requires further analysis when considering Quantitative Easing.

7 | APPLICATION OF TECHNOLOGY

The previously introduced proxies, as well as the theoretical pricing models, offer vast possibilities to apply technology in order to get fast and possibly more precise estimates of CDS premia. Different types of algorithms can, for example, improve the results of theoretical models or help rating agencies to enhance the rating's precision. In the aftermath of both the Financial Crisis and the Euro Crisis banks started to develop more accurate credit scoring models, based on statistical and machine learning methods.

The application of machine learning can be justified by the fact that it is possible to develop more dynamic models that are not based on rigid assumptions. Most of the research and application to date has been related to the estimation of credit risks, but the application can also be useful for the estimation of liquidity risk. According to Lessmann et al. (2015), the industry standard for credit risk estimations is the logistic regression, following alternative methods, such as Neural Networks are introduced. As Tavana et al. (2017) demonstrate, Neural Networks and Bayesian Networks are useful for banks to estimate liquidity risks.

As discussed, the influence of counter-party risk is negligible and often not measurable and is therefore not addressed by most market participants. Nevertheless, its occurrence should be considered, and further research is necessary to obtain a comprehensive understanding. It is conceivable, for example, to include a parameter for this risk in logistic regression.

Before available methods and their application are discussed a brief overview of the algorithms and the notations used in this paper is provided. Data is denoted in matrix form as

$$A_{m,n} = \begin{pmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,n} \\ a_{2,1} & a_{2,2} & \cdots & a_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m,1} & a_{m,2} & \cdots & a_{m,n} \end{pmatrix}$$

where each of the m-dimensional column-vectors represents a feature (or variables) and the n-dimensional row-vectors represent the observations. The vector of target values (or labels) is

$$y = \begin{pmatrix} y_1 \\ \vdots \\ y_m \end{pmatrix}$$

where $y_i \in \{0, 1\}$ denotes the class. The three classification algorithms presented approximate a function $f()$ so that $f(a) \approx y$ is satisfied and the observations are correctly labelled according to their class. Possible labels could be for example default/no-default, a range of default probabilities or a credit score such as rating agency's rating.

7.0.1 | Support Vector Machines

Support vector machines have been widely applied for credit scoring and were first introduced by Boser et al. (1992). A support vector machine performs a classification as the one described above by computing an m-1-dimensional hyperplane which maximises the distance between members of different classes. Figure 2 pictures a support vector machine in the 2-dimensional case, where there are two different classes (black dots and white dots).

Since the support vector machine's goal is to achieve the best possible prediction accuracy for testing data, the aim is to maximise the difference between the two dashed lines on the left and the right of the solid hyperplane. The intuition for the following proof is obtained from James et al. (2015). Let

$$w \times a - b = g(a) = y \tag{1}$$

be a random line in the 2-dimensional space. Then b denotes the displacement of the line relative to the origin, also called the bias, w denotes the normal vector that shows the orientation (rotation) relative to the origin, also called weight vector, of the random line and a denotes an m-dimensional point in the space (here: feature vector). Since support vector machines usually label their classes -1 and +1 we will follow this convention and get $y \in \{-1, +1\}$ for the two-class labels. Using y we can rewrite equation 1 as

$$w \times a - b = g(a) = -1 w \times a - b = g(a) = +1 \tag{2}$$

and we get the two dashed lines in figure 2. The support vector machine now optimises the weight vectors w in such a way that the distance between the closest members of the two classes is maximised. Since the vector w is perpendicular to its corresponding line and the lines themselves are fully defined, since the training observations a are known, we can calculate the distance between the two classes with $u = \frac{w}{\|w\|}$ the unit vector of w and m as the distance between the two hyperplanes from equation 2 we can define a vector k as:

$$k = m\frac{w}{\|w\|} \tag{3}$$

Using one of the hyperplane equations from above and the fact that every vector z can be written as

$$z = a_0 + k \tag{4}$$

where $a_0 = (0, 0)$ is the origin, we obtain

$$w \times z + b = 1 \leftrightarrow w \times (a_0 + m\frac{w}{\|w\|}) = 1 \leftrightarrow wa_0 + m\frac{\|w\|^2}{\|w\|} + b = 1 \leftrightarrow wa_0 + b = 1 - m\frac{\|w\|^2}{\|w\|} \tag{5}$$

Recalling that $w \times a_0 + b = -1$ we finally get

$$m = \frac{2}{\|w\|} \tag{6}$$

The problem of determining the maximum distance between two classes now can be solved as a constrained optimisation problem using the help of Lagrange multipliers

$$min_{w,b}\|w\| subject\ to\ y_i(wa_i + b) \geq 1 \tag{7}$$

where the equations can be summarised in equation 2 by using the assumption that $y_i \in \{-1, +1\}$. Now that the weight vector for equation 2 is obtained, the class of an unlabeled sample input a_{sample} can be computed using the solid line equation $w \times a + b = 0$. If the resulting value is larger than zero, class +1 is predicted and if the resulting value is smaller than, zero class -1 is predicted. For the multidimensional case, the proof works analogously except that the inner product between the weight vector and the training point is replaced by a kernel function, e.g. the radial basis function kernel.

7.0.2 | Artificial Neural Networks

Heaton (2015) states that neural networks consist of three different layer types: input layers, hidden layers and output layers. Each of these layers consists of several so-called neurons. The input layer is always the first layer in a neural network. A neural network has exactly one of them and the neurons in this layer are the values of the variables in the dataset, these inputs are denoted as x_i. The second type of layers is the hidden layers: Each neuron in the hidden layer receives the values form the variables form the input layer and calculates the function:

$$f(x_i, w_i) = \phi(\sum(w_i \times x_i)) \tag{8}$$

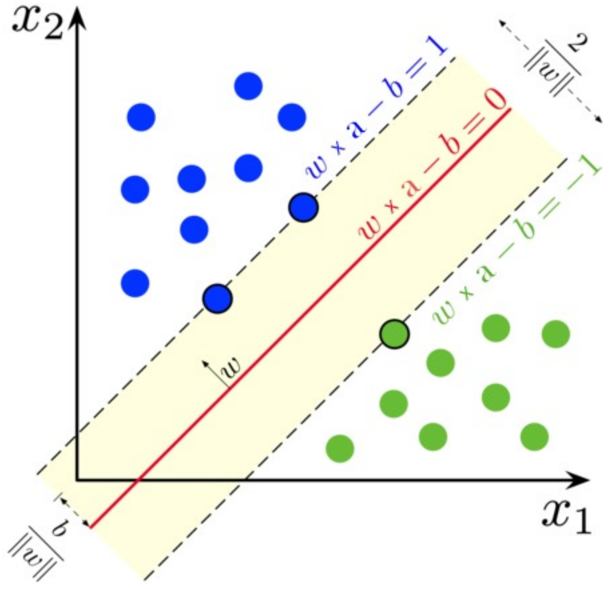

FIGURE 2 Distance Maximising Hyperplanes: *The plot shows the two distance maximising hyperplanes for the two classes. Maximising the distance $\frac{2}{\|w\|}$ is the same as minimising $\|w\|$. By computing the largest possible margin, classes can be distinguished clearly from one another* (Feser, 2020).

where w_i are the so-called weights and ϕ is the activation function.[5] Therefore, one can view a hidden layer neuron as a linear regression formula which gets passed to some function ϕ. The activation function here is the parametric rectifier linear unit (prelu) developed by He (2015) but others like the hyperbolic tangent or sigmoid can be used as well. The activation function has a significant effect on the overall performance of the neural network and must be chosen for each network individually. As the number of neurons is adjustable, so is the number of hidden layers.

The network's last layer is the output layer. The number of output neurons are the possible classes an observation can belong to, in a classification task. In such a case the particular output neuron returns a 1 if the observation is of class i and 0 otherwise. For an application with only two classes, the network has one output neuron which is active with the sigmoid function and returns a value between zero and one which can be viewed as the probability that an observation belongs to class 1.

The goal of a neural network is to estimate an unknown input's class based on the patterns of the training data. So the task of training a neural network comes down to minimising a loss function. A standard loss function is for example the mean squared error (MSE)

$$MSE = \frac{1}{n}\sum_{=1}^{n}(\hat{y}_i - y_i)^2 \tag{9}$$

which calculates the squared difference between a prediction $\hat{y}_i$ and the true value y_i over all training data n. Because $\hat{y}_i = f(w_i; x_i)$ (like in the case of linear regression), the key to minimising the error is adjusting the weights properly.

[5] cf. Heaton et al. (2015)

For adjusting these weights, the standard methods is called gradient descent following Heaton (2015):

$$w_{new} = w_{old} - \alpha \nabla l(w_i, x_i) \tag{10}$$

where $l(w_i, x_i)$ is the gradient of the loss function with respect to the weights. Furthermore, α is the so-called learning rate, a parameter that regulates how much the weights should be changed in each iteration. Graphically, one can see this procedure as finding the minimum of the loss function. Usually, calculating the gradient of the loss function for the entire data set is computationally expensive, so the gradient is normally evaluated for a small batch or sample of the training data, this method is referred to as stochastic gradient descent.

An optimal batch size is necessary for a well-performing neural network, as Keskar et al. (2016) show. After training the neural network (determining the weights), predictions are made simply by passing the variables of an observation to the input neurons and then calculating the function values of all hidden layer neurons and passing these to the output layer.

7.0.3 | Principal Component Analysis

Principal component analysis (PCA) refers to a method used for dimensionality reduction of data matrices A. James et al. (2015) describe PCA as finding the principal components of a dataset so that the maximum variance is obtained. The first principal component is a linear combination of the features a_i, denoted as

$$Z_1 = \phi_{11} a_1 + \phi_{21} a_2 + \ldots + \phi_{p1} A a_p \tag{11}$$

$$where \sum_{j=1}^{p} \phi_{j1}^2 = 1$$

which has the largest variance. After determining these coefficients we obtain the so-called loading vector[6] with elements ϕ_{j1}. This loading vector is the direction in the feature space in which the variance is maximised. The next principal components are computed analogous with the restriction that the previously computed component(s) must be uncorrelated with the new one. If the percentage of retained variance is plotted against the number of variables retained after principal component analysis, the resulting figure is called scree plot.

7.1 | Discussion

This section reviews how machine learning methods perform in classification tasks for the estimation of CDS premia and whether they might be used to further improve the accuracy of models currently used by financial services firms. This is to be determined on the basis of the current literature. The importance of such metrics was highltighrted by AIG at the time of the credit crisis. AIG was a major seller of CDSs at that time.

At the end of June 2008, AIG had outstanding CDS with a volume of approximately £275 billion without having secured itself for potential payments under the contracts. The unexpected increase in credit defaults caused AIG to experience severe payment difficulties. In such a case, the seller of CDSs may no longer be able to provide the promised insurance benefits.

[6] cf. James et al. (2015)

In September 2008 AIG had to be rescued by the US government. The example of AIG highlights how, along with the default risk of the underlying security, other risks such as counter-party risk and liquidity risk can influence the level of CDS premia. Knowing and understanding the determining factors of the premia is particularly important for investors who want to hedge against the default risk of the reference company, for political decision-makers who are considering additional regulations in CDS trading due to the financial crisis, and for analysts who can obtain useful information from the premia.

Bellotti and Crook (2009) use a credit card database to compare SVM's performance in the estimation of default risk against other approaches. Similarly, Li et al. (2006) find that SVMs for the task of credit scoring outperform Multilayer perceptron and Logistic Regression. Various studies show that SVMs can lead to more accurate predictions of credit default risks than other methods do, therefore they offer potential for further improved ratings. Nevertheless, the outperformance is not constant and depends on the dataset and calibration of the model. As Gündüz and Uhrig-Homburg (2011) state, the outperformance compared to Logistic Regression is mainly consistent, while Backpropagation Neural Networks are mostly outperformed over smaller datasets.

Several studies show that in the cross-sectional portion of the analysis, both Merton's Structural Model (1974), as well as Constant Intensity Models, outperform SVMs. However, for the time-series portion of the analysis, SVMs outperformed these. Gündüz and Uhrig-Homburg (2011) show that "in one-, five-, and 10-step-ahead predictions of time series the machine learning algorithm significantly outperforms financial models." It is possible that to achieve the best performance, a combination of different models is necessary. For example, a SVM that includes (implied) volatility, stock price development and historical CDS prices for the prediction of the CDS premia is a conceivable solution. Especially in combination with Structural or Constant Intensity Models results should be robust.

Before discussing artificial neural networks' performance in classification tasks for credit and liquidity risk, it should be noted that the neural networks discussed here are only a fraction of the various existing methods and therefore any findings should only be related to them. Using Merton's (1974) structural approach in combination with a Neural Network Angelini and Ludovici (2009) can generate a "forward-looking" valuation model for CDS. With matching financial data on the issuer with market related data the neural network achieves precise pricing for CDS.

A particular strength that will also be helpful in further developments is certainly the combination of different data sources. In particular, the input of real time data and the correct weighting of the various factors may enable even more accurate models in the future.

In the practical application of machine learning methods, above the rating agencies and the information service provider Bloomberg should be mentioned. They develop various pricing and analysis tools, often based on state-of-the-art algorithms.

The possibilities offered by the analysis of large amounts of data have recently been demonstrated in a number of computational economic studies, and special topics such as the determination of CDS premia can be answered more precisely and robustly with the help of these methods in the future. With all these developments, however, it is important to keep in mind the limitations and risks in order to avoid risks to the financial system as in 2008/2009.

It can be concluded from the current literature that for price estimates in the near future the classical Structural Models and Constant Intensity Models are performing better or as good as machine learning approaches, while for estimates in the distant future the latter perform better. One of the most important strengths of the application of machine learning techniques in CDS premia determination is certainly the ability to quickly adapt to new trends.

In the future, this could be, for example, the consideration of ESG risks in credit risk analysis and a rapid adaptation with regard to implications for CDS. Nonetheless, interest rate decisions or press conferences of central banks, for example, can be evaluated in real time and taken into account for pricing.

8 | CONCLUSION

This paper reviews the literature on Credit Default Swap Premia and their determination. It linked this to the application of machine learning techniques for the estimation of the same. It was shown that, with the help of CDS, it is possible to trade credit risks. They offer an opportunity to hedge against the default risk of companies and countries but are not as effciently priced as thsy could be.

We show which factors determine the premia. The default risk makes up the most significant part of the premium. Therefore, theoretical valuation models focus on this risk. Of the risk factors examined here, the debt ratio, the risk-free interest rate, the slope of the yield curve, volatility and rating have a statistically significant influence on the level of the premium. The higher the default risk, the higher the premium. The counter-party risk only has a minimal influence, which can almost be neglected by the use of collateral.

We observe that in turbulent market phases, such as during the last financial crisis, the risk gains in importance, but the influence on the level of premia remains very small. In principle, the higher the counter-party risk, the lower the premium. The liquidity risk influences the determination of the premium, especially during turbulent market phases. The risk factors examined here - bid-ask spread, number of transactions and number of buy and sell prices - have a statistically significant influence. However, when comparing the studies examined here, it is not entirely clear whether a decrease in liquidity leads to higher or lower premia. Hence, this topic requires further research.

It was shown that there is a close correlation between the CDS market and the corporate bond market. The premium corresponds roughly to the yield spread of the reference bond with the same maturity. Additionally, the research shows that the CDS market is generally price-leading compared to the corporate bond market.

We believe the combination of the presented proxies with machine learning methods opens a space for further research. A mix of models could help both academics and practitioners to achieve more precise premia determination in the future. This, in turn, can improve the understanding of the markets and increase the efficiency of the CDS market.

It is shown that SVMs perform strongly for more forward-looking models, still Structural and Constant Intensity Models can outperform machine learning approaches. The calibration of models is crucial, and based on the extensive studies in the field of credit risk analysis; the model selection is eased. It seems that especially the combination of neural networks with Structural Models offers vast possibilities for further research. Finally, new risks such as ESG can be incorporated into the models and help to increase awareness of evolving risks.

In conclusion, it can be stated that the determination of the influencing factors of CDS premia is a complex problem and that continually changing markets also alter the requirements on models for valuation. To cope with this transition, the use of different machine learning methods is recommended.

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